INCORPORATING HETEROGENEOUS CUSTOMER PREFERENCES WITH BAYESIAN METHODS FOR DECISION MAKING IN ENVIRONMENTALLY CONSCIOUS DESIGN

BY

YUAN ZHAO

DISSERTATION

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Doctoral Committee:

Professor Deborah Thurston, Chair
Associate Professor Ali Abbas
Assistant Professor Harrison Kim
Professor Michael Shaw

ABSTRACT

Global warming, greenhouse gas emissions, and product waste have serious impact on the balance of land, ocean, and air temperature. Environmentally conscious consumers and environmental protection legislation have been driving manufacturers to design, produce, and dispose products in a more environmentally responsible manner.

The purpose of environmentally conscious design and manufacturing is to develop methodologies for designing products from "green" principles, from conceptual design through consumer use and ultimately to the end-of-life management. Incorporating environmentally conscious design poses many challenges. The greatest challenge is how to change conventional design and manufacturing and ensure sustainable production systematically and cost effectively.

Progress has been made towards many environmentally oriented “Design for X” approaches, which target specific aspects of product life-cycle. One of the limitations of existing methodologies is that most approaches focus on minimizing the reprocessing cost or maximizing the recovery values only at the end-of-life management stage. However, less than one-third of the reprocessing costs depend on optimization of the reprocessing process, while the remaining costs are highly dependent on the early product design phase. Therefore, it is necessary to simultaneously consider the contradictive objectives in both the early design stage and the end-of-life stage. The goal of this work is to make design decisions early during the design process so that we can maximize the overall life-cycle value while minimizing costs and environmental impacts.

Product design is considered to be the most critical stage involving decisions that incorporate environmental design principles into product development. However, the increasing complexity of energy efficiency improvements and difficulty of its implementation in product design and manufacturing impose additional design constraints and costs, which are the major concerns for manufacturers. One of the biggest obstacles to the integration of environmental principles into product design is a lack of understanding about how customers respond to environmentally conscious design. To change customer buying behaviors for products with more environmentally friendly attributes, manufacturers need to understand customer preferences first. In addition, all consumers do not have the same preferences. Heterogeneous customer preferences require analysis at the individual level and prediction of market behavior by aggregating individual customer choices into market segment levels. The need for a quantitative assessment of the trade-offs between improved environmental attributes and other product performance in different market segments is a major task and a critical research topic in product design.

The methodology offers a framework where, driven by the interaction of heterogeneous customer preferences, product design decisions and end-of-life decisions are optimized under the constraints of product life cycle design. It can be expected that proposed approaches in this work will play an important role in the product life cycle design. It is envisioned that the models proposed in this work and case study results can provide manufacturers with relevant guidelines and useful insights regarding their optimal decision making in environmentally conscious design.

To My Family

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CHAPTER 1 INTRODUCTION

1.1 Background

Global warming, greenhouse gas emissions, and product waste have serious impact on the balance of land, ocean, and air temperature. Environmental protection legislation and environmentally conscious consumers have been driving manufacturers to design, produce, and dispose products in a more environmentally responsible manner [1].

Increased environmental legislation force manufacturers to employ environmentally conscious design and manufacturing methods. The environmental laws and legislations restrict the use of hazardous substances in electrical and electric products and promote manufacturers to collect and recycle their products. For example, under the Waste Electrical and Electronic Equipment Derivative (WEEE Derivative), which was enacted in law in Europe in 2003 [2], producers are responsible for providing financing for the collection, treatment, recovery and environmentally sound disposal of their End-of-Life (EOL) products. Following the WEEE Derivative, similar legislation has been implemented in other countries, like Japan, and in several states of the United States [3] [4] [5]. The emergence of these existing and anticipated product take-back laws is a major driving force for manufacturers to incorporate these considerations into product design. Manufacturers not in compliance with environmental regulations will incur monetary penalties or potential liability. Although the goal of many manufacturers is usually to comply with the law at the minimum possible cost, more and more manufacturers are committed to ensuring the highest standards of social and environmental responsibility wherever their products are made.

Largely motivated by energy and environmental concerns, customers, on the other hand, influence manufacturers' strategies and design processes by selectively purchasing products that have been shown to be environmentally benign. When it comes to "going green", consumers are increasingly turning to new alternative technologies promoted by the manufacturers. Environmentally benign design can greatly improve the "Green" image of a company and give significant competitive advantages to capture greater market share.

The objective of environmentally conscious design (also called sustainable design, environmental design, eco-design, green design, environmentally benign design etc.) is to "eliminate negative environmental impact completely through skillful, sensitive design" [6]. Correspondingly, environmentally responsible manufacturing is defined as "an economically-driven, system-wide and integrated approach to the reduction and elimination of all waste streams associated with the design, manufacture, use and/or disposal of products and materials" [7] [8]. While the practical application varies, in general, environmentally friendly technologies apply sustainable design principles and use low-impact materials, high energy efficient products, and can be reused or recycled at the end of their useful life.

Product design is considered to be the most critical stage involving decisions that incorporate environmental design principles into product development. However, the increasing complexity of energy efficiency improvement in product design and manufacturing impose additional design constraints and costs, which are major concerns for manufacturers.

One of the biggest obstacles to the integration of environmental issues into product design is the lack of understanding about how customers respond to environmentally conscious design. The need for a quantitative assessment of the trade-offs between improved environmental attributes and product performance is a major task and a critical research topic in product design. Environmentally conscious design eventually needs to make the transition into mainstream design, rather than stay in a high-profile niche application. Therefore, in order to stay competitive, sustainability innovation needs to begin with a deep understanding of consumers choice behaviors.

In addition, traditionally, the value of a product for manufacturers refers to the profit realized by selling a new product. Another type of value can be achieved through product recovery in product end-of-life management [9]. It has been recognized that the manufacturing cost and end-of-life management cost are highly dependent on product design phase. A good design paradigm from the environmental perspective is to "close the loop" through reuse, remanufacturing or recycling, rather than disposal.

Under such circumstances, manufacturers must "close the loop" for the lifecycle of products they make [10]. The product lifecycle is a collective term for the stages undergone by a product including raw material processing, manufacturing, transportation, product use, and end-of-life management. During the product lifecycle, the two stages of product usage and end-of-life have a major influence on the green life cycle of a product. The goal of lifecycle design is to make design decisions early during the design process that maximize overall life-cycle value while minimizing costs and environmental impacts [11].

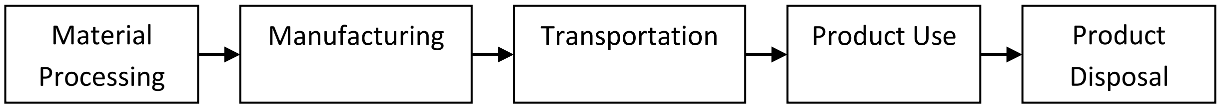


Figure 1-1: "Opened" product life cycle

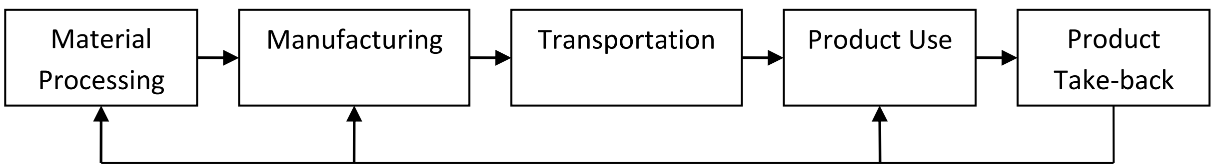


Figure 1-2: "Closed" product life cycle

When a product reaches the end of the product usage phase, End-of-Life design options often comprise several discrete choices, including direct reuse, remanufacture, recycle or disposal of components. Reuse can extend the useful life of the product or components, thus avoiding waste of the added value in the manufacturing process. Utilizing recovered products in a remanufacturing operation has other potential benefits in addition to compliance with legislation. Energy consumption, material requirements and environmental impacts might be lower than those for newly manufactured products. In this way, the manufacturers need to determine how to deal with these disposed products in the end of life cycle and conform to environmental friendly requirements.

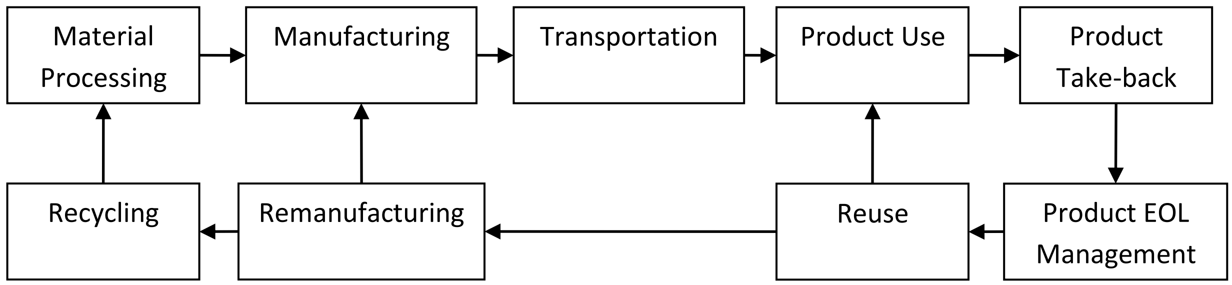


Figure 1-3: Product end-of-life management stage in product life cycle

1.2 Motivations and Research Objectives

1.2.1 Motivation for Integrating End-of-Life and Initial Profit Considerations in Product Life Cycle Design

Often before a returned product can be recovered, it must be disassembled, a process of physically separating an assembled product into parts and/or subassemblies for further reuse and recycling. Although this plays an important role in product end-of-life decision making, one of the limitations of existing methodologies is that many approaches focus on minimizing the reprocessing cost or maximizing the recovery values at the end-of-life management stage. It is recognized that almost 80% percent of a product's life-cycle costs and environmental impacts are decided during product design [12] [13]. In these studies, the product design is given as predefined configuration (a priori) and not considered in the optimization problem. Therefore, in order to improve the end-of-life management, new methods are needed to improve product design decisions in the early stage.

While some progress has been made in improving end-of-life (EOL) value through decision making in the early design stage, contradictive objectives make it difficult to simultaneously optimize initial sales profits and EOL value. To increase end-of-life values, it is necessary to consider design decisions for both the early design phase and the end-of-life phase simultaneously. The contradictive objectives in these two stages require simultaneous consideration of both stages.

The methodology proposed in this thesis attempts to overcome the limitations of existing approaches and offers a comprehensive strategy to simultaneously identify design decisions and end-of-life decisions in order to maximize profitability through the whole product life cycle. A mathematical model is developed to integrate end-of-life recovery value with product design decisions. The improvement of component reuse value or recycling value is achieved by linking design decisions in the early design stage with end-of-life decisions in order to maximize total product value across the span of the life cycle. A matrix based representation that can group components into several end-of-life modules with similar end-of-life decisions is also presented. Different design alternatives are compared to understand their influence on product lifecycle values. In addition, Decision-Based Design method is used here to helping manufacturers in simultaneously considering product early design decisions and its uncertainties along with the end-of-life values in the future.

1.2.2 Motivation for Determining Varying Lifecycle Lengths within a Product Take-back Portfolio

Remanufacturing systems are more complex than traditional manufacturing systems. Guide [14] analyzed several complicating characteristics and uncertainties that require significant changes in production and control activities for remanufacturing firms. The major sources of uncertainty are the timing and quantity of returned products and their components. Long range product planning can help the manufacturer make end-of-life (EOL) design decisions. Mangun and Thurston [15] developed an EOL decision model where a leasing program (where the manufacturer can control the timing of product take-back) facilitates component reuse, remanufacturing and recycling over multiple but static length lifecycles. Product take-back and reuse are sometimes at odds with the rapidly evolving desires of customers. "Selling a service" (rather than a product) through leasing enables the manufacturer to control the timing and quality of product take-back, but current methods assume a fixed leasing period. In addition, product take-back and reuse are sometimes at odds with the rapidly evolving desires of some customers. What is needed is a method for fine-tuning the time span of customers' life cycles in order to provide each market segment the combination of features it most desires.

I present a new method for performing long range product planning so that the manufacturer can determine optimal take-back timing, end-of-life design decisions, and number of lifecycles. The method first determines a Pareto optimal frontier over price, environmental impact and reliability using a genetic algorithm. Then, a multiattribute utility function is employed to maximize customer utility across different segments of the market, and also across different lifecycles within each segment. In addition, post-optimal studies help determine feasibility of component redesign in addition to parts consolidation.

1.2.3 Motivation for a Hierarchical Bayesian Method for Market Positioning in Environmentally Conscious Design

The purpose of Environmentally Conscious Design (ECD) is to develop methodologies for designing products from "green" principles, from conceptual design through consumer use, and ultimately to the End-of-Life (EOL) disposal [16]. Progress has been made towards many “Design for Environment” oriented approaches, which have been focused on specific aspects or the product whole life-cycle [17]. One of the limitations of existing methodologies is that most approaches focus only on engineering design decisions. However, certain engineering researchers have demonstrated the importance of integrating market considerations in engineering decision making. It is widely accepted that the design decisions should be made based on objectives at the system or enterprise level and marketing considerations [18] [19].

In addition, environmentally conscious design presents new challenges to designers. Sustainable materials and manufacturing processes often create extra costs relative to non-sustainable products. Sometimes designers need to make trade-offs on performance or value in an effort to make products more sustainable. However, environmentally conscious design eventually needs to make the transition into mainstream design, rather than stay in a high-profile niche application.

Therefore, in order to stay competitive, sustainability innovation needs to begin with a deep understanding of existing consumers choice behaviors.

As they attempt to achieve their sustainable innovation goals, manufacturers need to pay more attention to how customers respond to environmentally conscious design. To change customer buying behaviors for products with more environmentally friendly attributes, manufacturers need to understand customer preferences first. Consumer decision making is often multidimensional [20]. A product can be described as a set of attributes and a combination of levels of these attributes. Complex products such as automobiles and electronics often have hundreds of product attributes. Hence, an important decision that designers face is which attributes to consider and which attribute levels are best for each market segment. More importantly, it is critical to understand how attributes contribute to customer value.

Additionally, environmentally conscious design requires designers to understand and harness market mechanisms. One of the key issues is how to position environmentally conscious products in the marketplace. All consumers do not have the same preferences. Heterogeneous customer preferences require analysis at the individual level and prediction of market behavior by aggregating individual customer choices. Market segmentation is based on “a number of smaller homogenous markets, in response to differing preferences, attributable to the desires of consumers for more precise satisfaction of their varying taste [21]”. Customer behavior data have been widely used in market segmentation theory to identify and group customers. Discrete choice models, conjoint analysis, and related Hierarchical Bayesian methods have become widespread in marketing.

In this thesis, a Hierarchical Bayesian method is applied to integrate market considerations, which can be used to measure attribute weights and identify appropriate market segments in which customers value environmentally conscious design. The objective is to develop an integrative framework that can achieve four aims:

1) Identify market segments for grouping customers who share similar choice behaviors;

2) Select product attributes to be considered in each market segment;

3) Measure the weights of various product attributes;

4) Determine the target market segment in which customers value the environmentally conscious design the most, depending upon the probability of customers adopting the product.

1.2.4 Motivation for Incorporating Heterogeneous Customer Preferences with Dirichlet Process Mixture Model for Product Positioning in Environmentally Conscious Design

The greatest challenge for manufacturers is how to design the products to improve their environmental performance. Sustainable design, environmental friendly materials, and related manufacturing processes often create extra costs comparable to non-sustainable products. For example, the additional price premiums associated with hybrid vehicles can run at least $3,000 more than a comparable non-hybrid vehicle. Therefore, in order to change customer buying behaviors for products with more environmentally friendly attributes, manufacturers need to understand customer preferences first. Manufacturers can make optimal design decisions based on inference on customers' decision making models.

It is also recognized that consumers are heterogeneous in their response to different attributes for any given type of product or service. The assumption that all consumers have the same preferences does not hold in the real marketplace. The preferences for different attributes vary over people rather than fixed. The question arises: how customer preferences are distributed and whether a customer tends to purchase the environmentally friendly design. In addition, when preference heterogeneity is high, manufacturers may need to divide a target market into several segments, which contains customers with similar needs. Market segmentation is often used to group or segment a collection of customer preferences into clusters or market segments, so that those within each cluster are more closely related to one another than customers assigned to different clusters. Market segmentation and product positioning, which are highly related to each other are widely discussed in marketing research works. Product positioning takes place in a competition of different alternatives. In order to best satisfy preference and profit objectives, manufacturers need to react to preference heterogeneity by balancing the product attributes in different market segments.

The number of market segments, size of market segments, and preferences in each market segment are usually assumed to be a prior for the manufacturers in many studies. However, that is not always the case in reality. In addition, due to rapid technological innovations, product characteristics, and changing customer requirements, the static analyses conducted by using finite number of parameters may result in under-fitting or over-fitting the observed data when there is a misfit between the model complexity and the amount of data. In contrast to these studies, this paper reverts to nonparametric Bayesian model, in which the amount of information that can capture about the preference data can grow as the amount of data grows. Marketing sales data from customers taking actions enable us to produce posterior distributions for individual level parameters.

1.2.5 Motivation for a Market Driven Optimal Upgrading Decision Making Approach for Remanufactured Products in Product Lifecycle Design

Product take-back system in manufacturing companies seeks to find an attractive way of recapturing as much of the economic and ecological value as possible from already manufactured and used products. Possible end-of-life design decisions include reuse, refurbishing, remanufacturing, material or energy recycling, and disposal. Compared with material recycling or energy recycling which can recapture natural resources and prevent waste and potential harm from toxic materials, product reuse and remanufacturing offer more economic and environmental benefits. However, it is usually not practical or acceptable for customers that the returned products are directly reused. Remanufacturing is thus needed which is defined as an industrial manufacturing process in which a worn-out or discarded product is restored to like-new conditions. Remanufacturing involves “retaining serviceable parts, refurbishing usable parts, or replacing identical or reworked components from obsolete products”[22].

In general, the remanufacturing operations allow the manufacturers to expand their market shares by providing cheaper remanufactured products [23]. If the remanufactured product is indistinguishable from the new products, then the benefits of remanufactured product can be highly improved. For example, the disposable cameras have the same price with the new product but with lower cost [24]. However, currently, remanufacturing is only economically feasible in some product sectors [25].

Product reuse and remanufacturing are conducted on the basis of keeping original design variables and parameters. If used products or components are properly remanufactured in any form, manufacturers can achieve the ecological and economic advantages. For most components, the environmental impact is the lowest if they can be remanufactured in the new generation and the highest if they are disposed [26]. Besides the ecological advantages, the component recovery offers significant economic benefits. The reuse or remanufacturing of products can recover the value added on a component or product where materials, energy and labor were invested to manufacture in previous generations.

It is noted that many efforts have made contributions to product end-of-life (EOL) management to help manufacturers make appropriate product recovery design decisions and address related issues. Very little research dealing with the product upgrade strategies has emphasized on customer preferences in product lifecycle design, which are the major concerns for manufacturers and can determine whether producing upgraded products are profitable. Customer preferences need to be addressed in dealing with the product upgrade and the methodology should be proposed to enable manufacturers to determine the optimal product end-of-life strategies. Hence, the demand modeling for mapping heterogeneous customer preferences to product attributes is needed, in which product attributes are the aspects of a product that either partially or completely addresses a customer need. In addition, it is necessary to address the optimal strategies to consider introducing upgraded products in some market segments that consists of heterogeneous customers.

The objective of product upgrading is to improve product performance to maximize profits while minimizing the corresponding upgrading costs. In addition, another key question for the manufacturers is how to determine the optimal strategies for providing upgraded products in different market segments that consist of heterogeneous customers.

1.3 Organization of the Thesis

The remainder of this thesis is outlined as follows:

In chapter 2, I present research background and literature in environmentally conscious design, decision making in engineering design, and Bayesian methods.

In chapter 3, I propose a comprehensive strategy to simultaneously identify design decisions and end-of-life decisions in order to maximize profitability through the whole life cycle;

In chapter 4, I present a method for performing long range product planning so that the manufacturer can determine optimal take-back timing, end-of-life design decisions, and number of lifecycles;

In chapter 5, a Hierarchical Bayesian method is applied to integrate market considerations, which can be used to measure attributes weights and identify appropriate market segments in which customers value environmentally conscious design;

In chapter 6, I propose a framework for incorporating heterogeneous customer preferences with Dirichlet Process mixture model for product positioning in environmental conscious design.

In chapter 7, I propose a market driven approach for optimal decision making in remanufactured product upgrade, which can improve the product performance to maximize profits while minimizing the corresponding upgrading costs.

In chapter 8, this chapter reviews the main contributions of this thesis, concludes the thesis, and outlooks research works in the future.

CHAPTER 2 LITERATURE REVIEW

2.1 Environmentally Conscious Design

In order to control and improve particular characteristics of a product, design rules or methodologies are proposed to address a particular issue that is caused by, or affects the characteristics. Many efforts have been dedicated to develop design methodologies to support product design integrating manufacturing process, such as Design for Assembly [27], Design for Manufacturability [28], Design for Quality [29], Design for Variety [30], and so on [31].

In environmentally conscious design, various “Design for X” (DFX) analysis methodologies and tools in design considerations have also been developed to assist and evaluate different aspects of product design. In order to obtain useful components and/or materials, Lambert and Gupta [32] discussed the methodologies in Design for Disassembly (DFD) [33]. The joining and fastening methods are well suited not just for assembly process, but also for disassembly. In addition, the disassembly sequence generation, disassembly level, and disassembly optimization problems were formulated to maximize the recovery profits or minimize the costs in the disassembly process. Design for Remanufactuirng (DFRM) was proposed by Bras and Hammond [34], in which the metrics for evaluating remanufacturability from product features and the design insights can be given to product designers for improving the remanufacturability of a product. Ijomah et al. [35] provided the guidelines in design for remanufacturing from workshops undertaken in the UK. Seliger et al. [36] quantitatively considered combinations of all possible end-of decisions and multiple recycling objectives to support product Design for Recyclability

(DFR). Lee et al. [37] developed design chart including demanufacturing complexity metrics, in which the recyclability map can be used in design modularity selection, material selection, and disassembly to reduce product retirement costs. Xing et al. [38] proposed a design model for integrating product recyclability and end-of-life decisions, including product end-of-life decisions prediction, modular structure formation, materials and fasteners selection, and design alternatives recyclability evaluation.

The objective of Design for Environment (DFE) [39] [40] methodologies is to minimize the potential environmental impact throughout the product life cycle, within which the product is created, used, and discarded. Meanwhile, Design for Environment and Life Cycle Analysis are often used together to make design choices on product structure, material selection, and manufacturing processes. Life Cycle Analysis (LCA) requires estimation of environmental impacts throughout all the stages. LCA not only informs strategies that would otherwise be developed without consideration of the environment, but also pinpoints critical areas to focus upon in a product's lifecycle. Design for Life-Cycle (DFLC) targets the entire system within which the product is created, used, and discarded when making design decisions. Chu et al. [41] presented a framework that can reduce the environmental impact of product development at the system design stage, by combining product design, manufacturing, and the supply chain. In addition, it is also essential to make the optimal decisions not only for one lifecycle but for multiple lifecycles together. For example, Dunmade [42] discussed the concept of design for multi-lifecycles and its link with sustainable design, and applied this concept in the agro-industrial sector. Zhou et al. [43] presented a multi-lifecycle product recovery model, optimal retirement planning, and design selection methods. The method was illustrated via computer monitor and PC. The results can help manufacturers fully incorporate environmental issues in product design and lifecycle planning.

In general, the remanufacturing operations allow the manufacturers to expand their market shares by providing cheaper remanufactured products. If the remanufactured product is indistinguishable from the new products, then the benefits of remanufactured product can be highly improved. For example, the disposable cameras have the same price with the new product but with lower cost [24]. However, this is not the case with most other products because of dynamic changing customer preferences. This provides motivation for researchers to develop methodologies to determine optimal product upgrade strategies to satisfy the customer needs.

In order to extend the value life of the products, Shimomura et al. [44] first defined upgradable product as a product that can upgrade its functionality during operation and/or remanufacturing stages, then proposed design methodology for upgradable products (DFU) and two guiding principles: "functions independent" and "functions insensitive." Xing et al. [45] proposed a model to measure product potential upgradability in product remanufacturing context, in which the upgradability evaluation is based on three indicators: generational variety, fitness for extended utilization, and life cycle oriented modularity. Later, Xing et al. [46] developed the algorithms for configuring repairable, durable, or heavy-duty products. Xing et al. [47] proposed a Fuzzy model for evaluation of product upgradability and reusability in remanufacture.

In addition, the objective of many methods is to facilitate product recovery through improvement in the early design phase. Ishii et al. [48] proposed product retirement strategies in product life cycle design. These methods can help the designers specify the disassembly level and end-of-life intent for clumps of components in advance, take into account material degradation and compatibility information in the early stages, and make iterative changes to improve product design. Fukushige et al. [49] presented a methodology to evaluate scenario based modular structures from different lifecycle scenarios predetermined in early lifecycle design. The probability function formulation for module lifecycle options for resource efficiency is employed.

Product design decisions often involve conflicting or partially conflicting objectives [50]. The shortcomings of existing DFX methodologies are that these approaches put too much focus on a particular process or aspect but might negatively affect objectives in other conflicting aspects. Seliger et al. [36] provided an automotive design example. If more valuable and durable materials supporting ease of recycling are considered in the product design phase, the automobile might be much heavier, which increases fuel consumption and environmental impact. In addition, previous studies emphasized more on operational issues such as disassembly and remanufacturing process, while neglecting the heterogeneity in customer preferences for choosing these remanufactured or recycled products. Hence, new modeling methods and approaches are needed to address these issues.

2.2 Decision Making in Engineering Design

Product design and development can be defined as the complete process of identifying customer needs, design for manufacturing, prototyping, and industrial design in order to bring together the marketing, design, and manufacturing functions of the enterprise [51]. Decision-making is one of the most essential aspects in product design and development [52].

Product design and development are based on the assessment of customer needs and technical specifications. Designers must identify and convert customer requirements to specific engineering requirements. Methods such as quality function deployment (QFD) [53] [54] [55] have been applied to engineering design to link the customer preferences to technical specifications. Thus, the customer needs are converted into a set of functional requirements that will eventually be satisfied by the design parameters within the technical and economic constraints of the manufacturing environment. However, the complexity of practical problems regarding the customer needs and high dimensional technical measures limits its applicability.

Many efforts have also been dedicated to integrating product design methodologies with marketing and customer preferences. In the product design community, for example, Cook and Wu [56] presented S-Model in demand estimation and examined the model predictions in design alternative selection. Wassenaar and Chen [57] established the guidelines for integrating demand modeling and customer oriented engineering design attributes to predict expected profits. Michalek et al. [58] proposed the analytical target cascading (ATC) based formulation to coordinate the objectives in marketing, engineering design, and manufacturing planning sub problems. Pandey and Thurston [59] presented a copulas based methods to model demand estimation considering component reuse and remanufacturing. Kumar et al. [60] introduced a hierarchical choice modeling method that can incorporate heterogeneous customer preference data from multiple sources. MacDonald et al. [61] demonstrated the relationship between crux and sentinel attributes in users preferences by applying theory from behavioral psychology. In addition, many methodologies have been proposed to help make product selection and product line positioning decisions, which can provide a subset of profitable product variants to cover more market shares. Li and Azarm [62] [50] discussed the design selections for single products and product lines while considering customer preferences, uncertainties, and market competitions.

Various approaches have demonstrated the importance of applying utility theory in engineering decision making [50], [57]. Thurston et al. [63–71] pioneered in the use of multiattribute utility theory in making engineering design decisions. The multiplicative utility function [72] is widely used to evaluate the desirability of attribute tradeoffs. Decision-Based Design (DBD) framework [73] has been proposed to treat engineering design as a decision-making process that involves value maximization for both producer and end-user. Wassenaar et al. [74] proposed discrete choice analysis for demand modeling in Decision-Based Design framework, and a hierarchy of product attributes were linked with engineering design attributes.

However, incorporating environmentally conscious design poses new challenges in product design and development. The greatest challenge is to change conventional design and manufacturing and ensure sustainable production systematically and cost effectively. Environmentally friendly products sometimes increase design and manufacturing efforts and additional costs. Designers face many conflicting objectives and uncertainties to meet customer demands. Hence, the tradeoffs between environmental impacts and cost and quality need to be captured, analyzed and organized as design knowledge. Several proposed methods [75–78] can be used to assess the customer's actual willingness to pay for environmental protection. Ramani et al. [79] reviewed the state of the art in sustainability and product design, and emphasized the importance of integrating downstream life cycle data into eco-design tools. Shiau [80] integrated engineering design, market systems, and public policy into the design decision-making. In his work, plug-in hybrid vehicles are used in case study and design alternatives are suggested for different social targets. Skerlos et al. [81] analyzed the incentives, challenges, and inhibitors to the sustainable design, then discussed metrics, strategies, and evaluation methods that could have an important impact on sustainable design.

2.3 Bayesian Methods

Bayes' original theorem is applied to point probabilities. The simplest form of Bayes' Theorem follows immediately:

$$p(B|A) = \frac{p(B)p(A|B)}{p(A)} \tag{2.1}$$

In words, we assign the prior probability of $p(B)$ for the occurrence of the event B. By observing the occurrence of the event A, we are interested in the probability of B occurring given that A has occurred, which is the posterior probability $p(B|A)$.

In the Bayesian paradigm, Bayesian inference employs a prior probability over hypotheses to determine the likelihood of a particular hypothesis given some observed evidence. Let $X_1, X_2, \dots, X_n$ be random vectors and we observe data $x_1, x_2, \dots, x_n$. Suppose that the joint distribution of $X = (X_1, X_2, \dots, X_n)$ is unknown but belongs to a family of distributions $\mathbb{F}$

$$F \in \mathbb{F} = \{F_\theta : \theta \in \Theta\} \tag{2.2}$$

The family $\mathbb{F}$ is a statistical model; the set Θ is a parameter space. Given the data x and parameter θ, Bayesian analysis is facilitated through the prior probability $\pi(\theta)$ and the likelihood $p(x|\theta)$ to compute a posterior probability $\pi(\theta|x)$.

$$\pi(\theta|x) = \frac{p(x|\theta)\pi(\theta)}{\int p(x|\theta)\pi(\theta)d\theta}$$

$$\propto\ p(x|\theta)\pi(\theta) \tag{2.3}$$

Where $m(x) = \int p(x|\theta)\pi(\theta)d\theta$ is the marginal density of X.

However, it is often the case that the prior probability parameter θ depends on another parameter φ that is not mentioned in the likelihood. So the prior θ needs to be replaced by a prior $p(\theta|\varphi)$. In addition, the prior probability of parameter φ is required to estimate the posterior probability $p(\theta, \varphi|x)$.

$$p(\theta, \varphi|x) \propto p(x|\theta)p(\theta|\varphi)p(\varphi) \tag{2.4}$$

The Bayesian methods in marketing have become very popular in the context of discrete choice models and their applications to conjoint analysis [82]. Hierarchical Bayes has facilitated individual-level conjoint models, and deriving utilities from choice experiments has become very popular among those modeling product line decisions or new product introductions [83]. Hierarchical Bayesian approaches enable us to ask subsets of questions from a sample of customers and obtain useful posterior point estimates of the utility function for each market segment [84].

Various methods have been proposed in order to use all sources of responses to enhance the estimates of the part-worths for each consumer with limited data. The advantages of Hierarchical Bayesian methods are the estimations in individual-level models, which allow manufacturers to target individuals or market segments in a more accurate way. Yang and Allenby [85] presented a Bayesian spatial autoregressive discrete choice model to study the preference interdependence among individual consumers, in which patterns of heterogeneity were reflected in autoregressive specification. McCulloch and Rossi [86] developed finite sample exact likelihood analysis of Multinomial Probit model with correlated errors, where the algorithm was developed using a variant of the Gibbs sampler. Imai and Van Dyk [87] developed a set of new Markov Chain Monte Carlo algorithms for Bayesian analysis of the Multinomial Probit model. Based on the marginal data augmentation method, the algorithms shows similar fast convergence compared with available Bayesian methods but with a more attractive prior specification. Burda et al. [88] presented a Bayesian Mixed Logit-Probit Model for multinomial discrete choice. To eliminate the IIA property, the individual and alternative specific parameters are allowed to follow nonparametric density specification and multivariate normal distributions. The model is estimated by using a Bayesian Markov Chain Monte Carlo simulation technique with a multivariate Dirichlet Process (DP) prior on the coefficients with nonparametric density. Xu et al. [89] proposed the Bayesian approach with structured sparsity for collaborative inference in the Benefit segmentation problem of marketing theory and practice. The population-level and individual-level model is connected by introducing hierarchical layer and similarity graph/network.

In parametric models, the number of parameters is assumed in some finite set and the complexity of the model is constantly bounded even if the amount of sample size is unbounded. The limitations of traditional parametric models using finite number of parameters are under-fitting or over-fitting the observed data when there is a misfit between the model complexity and the amount of data [90]. This entails the need to use the nonparametric Bayesian model, which is referred to a Bayesian model on an infinite-dimensional parameter space [91]. Nonparametric models allow the number of parameters to grow with the number of sample size; the amounts of information that $\boldsymbol{\theta}$ can capture about the data D can grow as the amount of data grows [92]. In the context of Bayesian nonparametric models, the "infinite-dimensional" can be interpreted as "of finite but unbounded dimensions"[93]. For some nonparametric models, the parameter space can be factorized in such a way that

$$\Theta = \Theta_1 * \Theta_2 \tag{2.5}$$

Where Θ_1 is a finite-dimensional linear space and Θ_2 is an infinite-dimensional space; then the statistical model is called semiparametric. Bayesian inference requires assigning prior distributions to all unknown quantities in a model and then computing the posterior given data. By using a nonparametric prior, it allows us to gain flexible parameter distributions without under-fitting or over-fitting the data, better predicative performance, and more robustness against misspecification. The Dirichlet Process is one of the most popular prior used in nonparametric Bayesian models of data [94] [95]. The Dirichlet distribution is a distribution over the K-dimensional probability simplex, which is a generalization of Beta distribution. The Dirichlet is the conjugate prior of multinomial distribution. $(\pi_1, \dots, \pi_K)$ is Dirichlet distributed with parameters $(\alpha_1, \dots, \alpha_K)$ as shown in equation (2.6).

$$p(\pi_k|\alpha_k) = \frac{\prod_i \Gamma(\alpha_k)}{\Gamma(\sum_i \alpha_k)} \prod_{k=1}^{K} \pi_k^{\alpha_k - 1} \tag{2.6}$$

Where $\sum_k \pi_k = 1,\ \pi_k \geq 0$. A Dirichlet Process (DP) is a distribution over probability measures, which can be interpreted as "infinite-dimensional" Dirichlet distributions, i.e. each draw from a Dirichlet Process is itself a distribution. A random probability measure G follows a Dirichlet process with base distribution G_0 and positive strength parameter α if for any finite partition $(A_1, \dots A_n)$ is distributed with parameters $(\alpha G_0(A_1), \dots, \alpha G_0(A_n))$ as shown in equation (2.7) and (2.8). The base distribution G_0 is the parameter on which the nonparametric distribution is centered, while strength parameter α represents the strength of belief in base distribution G_0.

$$G \sim DP(\alpha, G_0) \tag{2.7}$$

$$\big(G(A_1), \dots, G(A_n)\big) \sim Dirichlet(\alpha G_0(A_1), \dots, \alpha G_0(A_n)) \tag{2.8}$$

The Bayesian approach also has a great variety of applications in product design and product recovery. Hoyle et al. [96], [97] proposed an integrated Bayesian Hierarchical Choice Modeling framework that addresses complex system design and considers system and random customer heterogeneity simultaneously. Wang et al. [98] proposed a design framework including evolving heterogeneous preferences and future market penetration for convergence products. The hierarchical Bayes model is used to evaluate heterogeneous choices to investigate the relationship between functionalities and customer preferences. Modular design representation can be integrated with design solutions to generate new design alternatives from existing product categories. Shun et al. [99] introduced a Bayesian framework to help designers to predict customer need distributions. The customer need can be updated through the forecast of external factors. In addition, Gutowski et al. [100] presented a Bayesian material separation model that can estimate the performance of the material separation process based on the material input data and probabilistic characteristics of separation process. Zhu and Deshmukh [101] applied Bayesian decision networks to investigate the impact of design decisions on product life cycle performance. Bayesian decision network provided a normative framework for representing and reasoning about decision problems under uncertainty in green design and manufacturing.

CHAPTER 3 INTEGRATING END-OF-LIFE AND INITIAL PROFIT CONSIDERATIONS IN PRODUCT LIFE CYCLE DESIGN AND UNDER UNCERTAINTY

3.1 Introduction

Growing concerns from customers and the government about product disposal highlight the necessity of improving product take-back systems to retain the embedded values in disposed products. Progress has been made towards minimizing the cost of the disassembly process. While some progress has been made in improving end-of-life (EOL) value through decision making in the early design stage, contradictive objectives make it difficult to simultaneously optimize initial sales profits and EOL value.

The increasing productivity of modern industry also means a fast growing surplus of waste, especially electronic waste, around the world. This presents a threat to the environment, which not only raises concern from customers, but also directly affects manufacturing profitability, since product take-back legislation often involves the producer directly. Under such circumstances, manufacturers must “close the loop” for the lifecycle of their products. The product lifecycle is a collective term for the stages undergone by a product including raw material processing, manufacturing, transportation, product use, and end-of-life management. Traditionally, the value of a product for manufacturers refers to the profit realized by selling a new product. Another type of value can be achieved through product recovery in product end-of-life management. A good design paradigm from the environmental perspective is to “close the loop” through reuse, remanufacturing or recycling, rather than dispose. Reuse can extend the useful life of the product or components, thus avoiding the waste of the value-added by the manufacturing process. Recycling can also prevent waste of potentially useful materials.

Often before a returned product can be recovered, it must be disassembled, a process of physically separating an assembled product into parts and/or subassemblies for further reuse and recycling [32]. This plays an important role in product end-of-life decision making. Therefore, considerable attention has been given to maximizing the recovery profits or minimizing the costs from the disassembly process.

Three main optimization problems are found in the disassembly process literature [102]. The first is the disassembly sequence problem, regarding the order in which to separate the components or subassemblies. It includes the identification of feasible disassembly sequences and determines the optimal sequence. Lambert [102] proposed a disassembly transition matrix using linear programming to solve optimal disassembly sequence problems. Giudice and Fargione [103] developed two different algorithms to optimize service-oriented and recovery-oriented disassembly planning. The second problem is to determine the depth of the disassembly process by reducing any further disassembly operations before recovery cost-benefit curves decrease. Peng and Chung [104] developed a methodology to determine the optimal selective disassembly planning for product maintenance issues. The third problem is the disassembly scheduling problem, including the optimization problems to satisfy the demand for disassembled parts and subassemblies while considering the system capacity and uncertainty [105].

While these approaches attempt to optimize the disassembly process, they do not address the issues related to design and end-of-life strategies simultaneously. In these studies, the product design is given as predefined configuration (a priori) and not considered in the optimization problem. However, Pnueli and Zussman [106] pointed out that only 10 - 20% of the recycling costs depend on recycling process optimization, while the remaining costs are highly dependent on the early product design phase. Therefore, in order to enhance end-of-life management, new methods are needed to improve product end-of-life values via early product design decisions.

Several efforts have been made to develop design methodologies to support product design for end-of-life management, such as Design for Disassembly [102], Design for Remanufacturing [34] [35], and Design for Recycling [36]. A detailed survey of literature in environmentally conscious manufacturing and product recovery (ECMPRO) is presented by Ali Ilgin and Gupta [16]. The objective of many methods is to facilitate product recovery through improvement of the early design phase. Ishii et al. [48] proposed product retirement strategies in product life cycle design. The results can help the designers specify the disassembly level and end-of-life intent for clumps of components in advance, consider material degradation and compatibility information in the early stages, and make iterative changes to improve product design. Fukushige et al. [49] presented a methodology to evaluate scenario based modular structures from different lifecycle scenarios predetermined in early lifecycle design. The probability function formulation for module lifecycle options in resource efficiency is employed. However, product design decisions often involve conflicting or partially conflicting objectives [50]. Seliger et al. [36] provided an automotive design example. If more valuable and durable materials supporting ease of recycling are considered in the product design phase, the automobile might be much heavier, which increases fuel consumption and environmental impact. Kwak et al. [107] proposed a methodology to design a product eco-architecture that can improve disassembly and recycling efficiency. The model can facilitate end-of-life management through product architecture an improvement. Behdad et al. [108] presented a model to consider sharing disassembly operations in order to improve the end-of-life strategies for multiple products. Kawk and Kim [109], [110] proposed models to evaluate end-of-life profits by considering product family and network design.

To increase end-of-life values, it is necessary to consider design decisions for both the early design phase and the end-of-life phase simultaneously. The contradictive objectives in these two stages require simultaneous consideration of both stages. The methodology proposed here attempts to overcome the limitations of existing approaches and offers a comprehensive strategy to simultaneously identify design decisions and end-of-life decisions in order to maximize profitability through the whole life cycle.

The section is organized as follows: Section 2 describes the problem formulation for the proposed methodology. Section 3 presents an illustrative example of product design and end-of-life management of cell phones, and section 4 summarizes and concludes.

3.2 Decision Model Formulation

In this section, a design decision model is built to link the product useful life and end-of-life stages, which can help manufacturers to make optimal design decisions to maximize profits from the whole product lifecycle point of view.

The design decision variables include two parts: a vector of design variables $\boldsymbol{x}$ in the product configuration stage, and projected end-of-life decision strategies $y_{k,l}$ for disassembled modules k ($k = 1, \dots K$) with end-of-life options l ($l = 1,2,3$). During end-of-life management, the set of components $S = \{c_1, c_2, \dots, c_n\}$ is divided into several end-of-life modules, which are defined as a set of components sharing the same end-of-life decision. Then the set of end-of-life modules is a partition of the set of components S into disjoint sets ($S = \cup_k S_k$). Here, the vector of design variables $\boldsymbol{x}$, including component materials, dimensions (e.g. height, length, width), and other technical specifications (e.g. capacity of the hard drive), is modeled to measure the product attributes upon which customers make their purchasing decisions. In addition, a product end-of-life value recovery model is also formulated to establish the relationship between product configuration decisions and end-of-life values for recovered components or modules.

In this paper, maximization of the net present value (*NPV*) function (V) of profit over the product lifecycle is the objective, as shown in equation (3.1). It includes two primary sources of profit: initial sales and end-of-life management. Profits from initial sales depend on product demand (D), selling price (P), and incurred manufacturing cost (C_M), which includes design and investment, manufacturing, logistics, material, and overhead cost. The second part of the objective estimates the end-of-life profit, discounted over the appropriate timeframe. It is assumed for purposes of illustration that manufacturers can take most of the sold products back for end-of-life management through leasing or other extended producer responsibility mechanisms. The recovered profits during the end-of-life stage are highly dependent on the condition of the products, recovered revenues (R_{EOL}) and reprocessing costs (C_{EOL}, C_D, C_{CT}) associated with various fractions of materials or components. In equation (3.1), r is interest rate and t is the average return time (years). Q is the amount of returned product received by the manufacturers for management.

Objective Function:

$$Max\ V = D(P - C_M) + \frac{1}{(1+\gamma)^t} Q(R_{EOL} - C_{EOL} - C_D - C_{CT}) \tag{3.1}$$

Initial sales profits are generated by the difference between price and manufacturing cost, multiplied by demand, which is estimated using the discrete choice model [111]. Various approaches have demonstrated the importance of integrating a discrete choice model with demand modeling in engineering decision making [18] [19] [112]. The new product is assumed to be launched in a specific market segment, which is composed of a choice set with the number of q products available to customers having similar choice behaviors. According to the random utility models, when customer *n* chooses a product alternative q, the utility function U_{nq} can be decomposed into two parts:

$$U_{nq} = V_{nq} + \varepsilon_{nq} \tag{3.2}$$

Where V_{nq} is the observed utility and ε_{nq} is the unobserved factors that affect utility but are not considered in V_{nq}. Under the assumption that the term ε_{nq} is independent and identically distributed (iid) with extreme values distribution for all q, the logit choice probability p_s is obtained as follows.

$$p_s = \frac{e^{V_s}}{\sum_q e^{V_q}} \tag{3.3}$$

The observed utility V_s is expressed as a function of deterministic linear coefficients $\beta' s$ and observed vector $\boldsymbol{z}$, which include price and product attributes ($\boldsymbol{F}$).

$$V_s = \boldsymbol{\beta}^{\boldsymbol{T}} \boldsymbol{z}_{\boldsymbol{s}}(P, \boldsymbol{F}) \tag{3.4}$$

The product attributes can be viewed as the aspects or functions of a product that partially or completely address customer needs and are defined as functions (f_F) of design vector $\boldsymbol{x}$ in the engineering product development process.

$$\boldsymbol{F} = f_F(\boldsymbol{x}) \tag{3.5}$$

The product price is the sum of total manufacturing and profit margin; profit margin included in the final price is a certain percentage of the manufacturing costs. The estimation of manufacturing costs is expressed as the sum of variable costs (C_V) and fixed costs (C_F). The variable costs are a function of material choice, dimensions, manufacturing process and labor costs depending upon decisions made for decision vector $\boldsymbol{x}$. Fixed costs C_F are treated here as constant for simplicity.

$$C_M = C_V + C_F \tag{3.6}$$

Then the expected product demand is represented as a function of market size (M) and the logit choice probability p_s, as shown in equation (3.7).

$$D = M \cdot p_s(\boldsymbol{\beta}, z(P, \boldsymbol{F})) = M \cdot \frac{e^{\beta^T z_s}}{\sum_q e^{\beta^T z_q}} \tag{3.7}$$

In addition, the design decision vector $\boldsymbol{x}$ is generally constrained to a set of technical equality $h(\boldsymbol{x})$and inequality constraints $g(\boldsymbol{x})$, which ensure that the decision vector maps to a feasible design.

$$h(\boldsymbol{x}) = 0 \tag{3.8}$$

$$g(\boldsymbol{x}) \leq 0 \tag{3.9}$$

The estimate of end-of-life management costs includes three parts: average collection and transportation costs C_{CT}, disassembly costs C_D, and reprocessing cost for end-of-life modules. Collection and transportation costs are assumed to be constants, since the optimization of reverse logistics in product take-back systems is outside the scope of this paper.

Product disassembly is a labor intensive process, and is performed manually in many situations. In the assembly process, components are connected with each other through physical joints, fasteners, or connections. However, the disassembly process is not simply the reverse of assembly process. A number of studies have shown that complete disassembly is infeasible and ineffective in product end-of-life management. Then the question becomes how to efficiently disassemble products in order to achieve valuable end-of-life modules. Gonzalez and Adenso-Diaz [113] developed a model to determine end-of-life strategy based on the product structure and the geometrical joining relationship among components. The product structure in 3D CAD representation and bill of materials (BOM) can be input into the model. Lai and Gershenson [114] also developed a product representation model, including a process similarity matrix and process dependency matrix to improve efficiency in the product retirement process.

In this paper, an end-of-life module disassembly matrix (EMDM) is proposed. It is a matrix representation of a product by which the headings of rows and columns represent the components. The initial product modular structure is reflected in the matrix based on the physical connectivity of components, as shown in figure 3.1 a). In this matrix, the interactions are the connections or joints that connect the modules or components. After the original product structure matrix is constructed, the next step is to rearrange the components, connecting them with those with similar end-of-life decisions. As shown in figure 3.1 b), the disassembly process is described by a sequence of actions that disassemble the connections between different end-of-life modules ($i \in S_k, i' \in S_{k'}$). An end-of-life module has a particular EOL disposition, which means all of the components in that module would have the same decision. Methods for estimating the disassembly time have been addressed in several papers [115] [113] [116]. The optimal time to disconnect components is dependent on joint type, accessible directions, positioning, and so on. Here, $\mathrm{t}_{\mathrm{i,i'}}$ is used to represent the disassembly time to separate component i and component i′. It is assumed to be a symmetric matrix.

For purposes of illustration, it is assumed that disassembly cost is proportional to disassembly time. The disassembly cost C_D incurred can thus be calculated based on unit time labor cost C_L and disassembly time $t_{i,i'}$, for $i \in S_k, i' \in S_{k'}, i < i'$.

$$C_D = \sum_i \sum_{\substack{i' \\ i<i'}} C_L * t_{i,i'} \tag{3.10}$$

There are several advantages to this approach. First, the matrix based representation can employ some clustering methods (Such as Design Structure Matrix (DSM)) used in engineering design

[117]. The matrix represents complex products with a large number of assembled components, and can be easily segregated into sub-matrices (subassemblies), in which the connections between the components are retained to avoid unnecessary further disassembly. Second, the sub-matrices can represent the precedence relationships between the subassembly and components. In order to separate the components within the sub-matrix, the sub-matrix needs to be disassembled from the product or some higher level sub-matrix first.

However, a major difference between the clustering methods for the end-of-life module disassembly matrix and other clustering methods in engineering design is that its objective is not to simply minimize the number of connections outside the partitioned modules. Instead, to determine the optimal depth of disassembly, it is also necessary to link this optimization problem with the end-of-life strategies for these modules. The profits (positive or negative) are based on the recovery profits (R_{EOL}) and reprocessing costs (C_{EOL}) associated with decisions for each module ($k = 1, \dots, K$), as shown in equation (3.11). The controllable binary (0-1) design decision variable set $y_{k,l}$ is defined to represent the end of life options l for module k. The decision variables include three possible end-of-life options -- reuse, material recycling and disposal -- for each module as discussed below. Equation (3.12) indicates that each module undergoes only one of the three end-of-life operations.

$$R_{EOL} - C_{EOL} = \sum_{k=1}^{K} \sum_{l=1}^{L} \left(R_{k,l} - C_{k,l}\right) y_{k,l} \tag{3.11}$$

$$\sum_{l} y_{k,l} = 1 \tag{3.12}$$

l=1,2,3 for $k = 1 \dots K$

	1	2	3	4	5	6	7	8	9
1	X	$t_{1,2}$				$t_{1,6}$	$t_{1,7}$		
2	$t_{2,1}$	X		$t_{2,4}$			$t_{2,7}$		
3			X	$t_{3,4}$			$t_{3,7}$		
4		$t_{4,2}$	$t_{4,3}$	X	$t_{4,5}$		$t_{4,7}$		$t_{4,9}$
5				$t_{5,4}$	X	$t_{5,6}$			
6	$t_{6,1}$				$t_{6,5}$	X			
7	$t_{7,1}$	$t_{7,2}$	$t_{7,3}$	$t_{7,4}$			X		
8								X	$t_{8,9}$
9				$t_{9,4}$				$t_{9,8}$	X

a) Initial Product Structure Matrix

	1	6	5	4	2	3	7	8	9
1	X	$t_{1,6}$			$t_{1,2}$		$t_{1,7}$		
6	$t_{6,1}$	X	$t_{6,5}$						
5		$t_{5,6}$	X	$t_{5,4}$					
4			$t_{4,5}$	X	$t_{4,2}$	$t_{4,3}$	$t_{4,7}$		$t_{4,9}$
2	$t_{2,1}$			$t_{2,4}$	X		$t_{2,7}$		
3						X	$t_{3,7}$		
7	$t_{7,1}$			$t_{7,4}$	$t_{7,2}$	$t_{7,3}$	X		
8								X	$t_{8,9}$
9				$t_{9,4}$				$t_{9,8}$	X

b) Disassembly Module in Disassembly Matrix

Figure 3-1: End-of-life module disassembly matrix

Reuse

Reuse is a lifecycle design option with generally higher environmental efficiency than other options. The component and/or module are disassembled from the product, undergo only minor cleaning and refurbishing, and are reused for its original function [118]. Components can generally be reused only if they retain their full functionality, but physical and/or technical obsolescence sometimes limits reuse. Hence, the evaluation of the remaining value and quality of reusable components is indispensable for determining the appropriate end-of-life strategies. The recovered profits from reusing module k are determined by the reuse value (or resell value) and related cost of this module, as shown in equation (3.13)

$$R_{k,1} - C_{k,1} = \theta_k * C_{V,k} - C_{k,U} \tag{3.13}$$

where $C_{V,k}$ is the manufacturing costs of a new module k; θ_k, which is between 0 and 1, is the depreciation factor reflecting manufacturers' perceptions about the remaining value of the module k; θ_k is defined based on both physical and functional obsolescence considerations, with higher θ indicating manufacturers with higher willingness to pay for the reused module. $C_{k,U}$ is the corresponding reuse processing cost including cleaning, sorting, etc.

Material Recycling

Material recycling is the process by which discarded materials are collected, sorted, shredded, and undergo a reforming process. Dahmus and Gutowski [119] developed a cost estimation model for recycling systems using Shannon's information theory methods. The model can measure the material values and mixture to determine the material recycling potential for different products in their end-of-life stage. Another important aspect in material recycling is material compatibility issues.

Here, recovery profits from the recycling process are based on the material composition and the ability to separate materials from the material mixture in the product, as shown in equation (3.14),

$$R_{k,2} - C_{k,2} = \sum_p m_p Pr_p - \sum_p m_p C_{c,p} \tag{3.14}$$

Where m_p is the total mass (g) of material p in module k; the material mixture in module k is dependent on material choice in each component belonging to this module. Pr_p is the projected future unit market price (\$/g) of the material p; $C_{c,p}$ is the projected future unit recycling processing cost of the material p. The right hand side of equation (3.14) represents the market value of recycled materials in the module k minus the processing costs of extracting and isolating each single material. Generally, a greater number of material types in the module will increase processing cost, which would be reflected by the parameter $C_{c,p}$ in the model.

Disposal

Disposing and dumping components of products without any recovery wastes resources and the value-added during manufacturing, and adds disposal costs based on the materials in the module as shown in equation (3.15), where $C_{D,p}$ is the projected future landfill cost per unit mass of the material p.

$$R_{k,3} - C_{k,3} = 0 - \sum_p m_p C_{D,p} \tag{3.15}$$

In addition, the impact of existing and potential legislation for product disposal should be considered. For example, the direct disposal of electronic waste is currently banned in several states because of the toxic materials some components contain. In this case, the projected future disposal rate would be very high as it is defined as hazardous waste.

Note that a major difference between the model presented in this paper and previous work is that the end-of-life values and costs are directly linked to the design decisions in the early stages in the integrative optimization model as they are all highly dependent on the design variables $\boldsymbol{x}$.

In addition, integrating design decisions over the whole product lifecycle give manufacturers new challenges due to the uncertainties associated with risks in different stages of the product lifecycle. It is especially evident in design decision making for large-scale product manufacturing. Decision-Based Design method [73] [57] is used here to help manufacturers in simultaneously considering product early design decisions and its uncertainties along with the end-of-life values in the future. It is necessary to use value function when there is no uncertainty and utility function otherwise. Instead of assuming the decision maker wants to maximize the expected monetary values, utility theory assumes that decision maker wants to maximize the expected value of utility in equation (3.16).

$$E\big(U(V)\big) = \sum_v P(V = v)U(v)$$

$$= \int_{v_{min}}^{v_{max}} U(v)f(v)dv \tag{3.16}$$

The single attribute utility function is used in here with an exponential form as shown in equation (3.17).

$$U(v) = a - be^{-v/\tau} \tag{3.17}$$

Where constant a and b can be chosen to normalize the utility function such that $U(v_{min}) = 0$ and $U(v_{max}) = 1$, where the value function (V) under consideration many range over the interval$v_{min} \leq v \leq v_{max}$. The manufacturers are assumed to be risk averse decision makers, where constant τ is the risk-tolerance constant. The single attribute utility function and scaling constants can be assessed using the lottery methods as described by Keeney and Raiffa [72].

3.3 Case Study and Results Discussion

This section demonstrates the model using a cell phone design example; however, the general model structure can be applied to other products as well.

Cell phones are an important part of fasting growing disposed E-waste stream of used electronics. Over three billion people around the world own cell phones, which are frequently replaced as new innovations launch in the market. As of 2009, over one billion cell phones wait to be recycled in the US, and more than 160 million will be added this year, and even more the next year [120]. Cell phone recycling can not only prevent environmental problems, but can also yield profit through reuse and recovery. Approximately 60% of end-of-life cell phones have resale value as refurbished phones, and the remaining 40% can be processed to recover precious metals through material recycling [121].

In the demand model, a hypothetical market is assumed with five product competitors and their attributes as shown in table 3.1. These data were collected from some real products in the current cell phone market. Six attributes are considered by customers in this market: Price (P), Weight (F_W), LCD size (F_L), Battery Capacity (F_B), Processor Speed (F_P), and Camera Pixels (F_C). The operating system or other software applications are not considered in this example. The total number of customers who are interested in buying a new product (market size) is 1 million. When a new product is launched in this market, the market share of existing products would be changed.

Table 3-1: Product competitors and their attributes in a cell phone market

Attributes	Product Competitors				
	Q1	Q2	Q3	Q4	Q5
Price ($)	129	169	199	229	349
Weight (g)	90	100	130	140	180
LCD size (inch)	2.4	2.8	3.2	3.5	4.1
Battery Capacity (Ah)	0.9	1.15	1.22	1.4	2.1
Processor Speed (GHz)	0.195	0.33	0.624	0.8	1
Camera (Megapixels)	1.92	2	3.15	3.2	6

Based on customers purchasing behaviors and goodness of fit estimates, the product attribute coefficients can be estimated in the logit model. In this case study, the coefficients are shown in table 3.2. They are consistent with customers' preference behavior for different attributes. In general, customers prefer lower price and weight (with negative coefficients), and higher product performance attributes (with positive coefficients).

Table 3-2: Attribute coefficient used in logit model

Attributes	Coefficient (β)
Price/100 ($)	-0.558
Weight/100 (g)	-0.85
LCD size (cm)	0.509
Battery Capacity (Ah)	0.402
Processor Speed	0.378
Camera (Megapixels)	0.109

The cell phone considered in the example is composed of the following major components: (1) Front Cover, (2) Display, (3) Keyboard, (4) Camera, (5) Speaker, (6) Antenna, (7) Main Board, (8) Processor, (9) Memory, (10) Battery, and (11) Back Cover. The product design variables $\boldsymbol{x}$ in the early design stage include:

x_1 = Material choice of cover;

x_2 = The width of display;

x_3 = The height of display;

x_4 = The width of battery;

x_5 = The height of battery;

x_6 = The length of battery;

x_7 = The choice of the processor;

x_8 = The choice of the camera.

Design inputs and constraints:

A model for the cell phone design that expresses the relationship between these design variables $\boldsymbol{x}$ and the observed product attributes is defined as follows.

The cell phone design has specified dimensions of width W_c = 60mm, length L_c = 115mm, and height H_c =12mm. The design variables are a mixture of discrete and continuous variables. The relationship between design variables and product attributes is described in detail in the following discussion.

The cover of a cell phone packages its components and provides basic protection. An ideal cell phone cover is not only robust to physical damage but also light weight as consumers prefer a lighter phone. Two types of materials are considered here: plastic and aluminum alloy. Plastic is usually a blend of PC and ABS, which is lighter and less expensive than aluminum but less durable. Aluminum alloys are alloys in which aluminum is the predominant metal and other elements are added. The weight-to-volume ratios of plastics and aluminum alloy are assumed as constants. Table 3.3 shows several estimated parameters for the two materials under considered, in which the data were collected from relevant literature and online websites. The weight of the covers $F_{W,1,11}$ and costs are calculated based on equations (3.18) and (3.19), which are dependent on the material choice -- binary decision variable x_1.

$$F_{W,1,11} = x_1(r_{C_P}W_{C_P}(l_{1_P} + l_{11_P})L_{c_P}(h_{1_P} + h_{11_P})H_{c_P}) + \\ (1 - x_1)(r_{C_A}W_{C_A}(l_{1_A} + l_{11_A})L_{c_A}(h_{1_A} + h_{11_A})H_{c_A}) \tag{3.18}$$

$$C_{V,1,11} = (x_1C_{1,P} + (1 - x_1)C_{1,A})F_{W,1,11} \tag{3.19}$$

Table 3-3: Parameters of materials used in the cell phone cover

	Plastics (PC/ABS)(P)	Aluminum Alloy(A)
Weight-to-volume ratio r_C (g/cm^3)	1.27	1.96
Front Cover Dimensions $W_c * l_1 L_c * h_1 H_c$ (mm^3)	60*40*1	60*40*0.7
Back Cover Dimensions $W_c * l_{11} L_c * h_{11} H_c$ (mm^3)	60*115*1	60*115*0.7
manufacturing cost ($/g)	1.01	1.1
recycling values ($/g)	-0.16	0.10

The display is an important component of the cell phone because it is the interface that provides visual feedback to the user. Due to the increasing demand for multimedia features, the display quality accounts for a large part of its value. A display is desired with bigger size, higher resolution, better technology, and higher color quality, which consumes more energy and costs more. So the design of a display is a tradeoff among these attributes. In this example, thin film transistor liquid crystal displays (TFT LCDs) is used with the width (x_2) and length (x_3) as the design variables. The resolution is assumed to be proportional to the area of the display since the number of pixels per square millimeter is fixed for all designs. The dimensions are constrained by the dimensions of the cell phone, as shown in equation (3.20)-(3.22). k_2, k_3 are the scaling factors for the dimensions and equal to 0.94, 0.83 separately. The aspect ratio of the display is assumed to be 4:3 if it is less than or equal to 3 inches, and 3:2 if it is more than 3 inches.

$$x_2, x_3 \geq 0 \tag{3.20}$$

$$x_2 \leq k_2 W_c \tag{3.21}$$

$$x_3 \leq k_3 L_c \tag{3.22}$$

The LCD size (F_L) is its diagonal length and represented in inches, as shown in equation (23). The cost of display is mostly determined by the size of the display. Based on the data collected from relevant literature [122] [123] [124] [125], the weight ($F_{W,2}$) and manufacturing cost ($C_{M,2}$) of the LCD display is given by equation (3.24) and (3.25).

$$F_L = \sqrt{0.01x_2^2 + 0.01x_3^2}/2.54 \tag{3.23}$$

$$F_{W,2} = 2.083 * (0.1x_2 * 0.1x_3 * 0.6) \tag{3.24}$$

$$C_{V,2} = 14.99 * F_L^2 - 70.089 * F_L + 103.62 \tag{3.25}$$

The rechargeable battery is another important component, as it provides power to support the operation of the cell phone. The increasing number of multimedia features requires longer battery life, which is one of the most important factors determining customer choice. Capacity is employed to describe battery life. It is measured in Ah (ampere hours, or mAh, milliampere hours). Given that the energy density of a certain battery technology is fixed, the capacity of a battery is determined by its size. However, the dimensions of the battery are constrained by the dimensions of the cell phone. The decision variables x_4, x_5, x_6 are the width, height, and length of battery which are greater than zero and less than the maximum space in the cell phone, which is represented in equations (3.26)-(3.29). k_4, k_5, k_6 are the scaling factors for the dimensions and equal to 0.84, 0.59, 0.53 separately.

$$x_4, x_5, x_6 \geq 0 \tag{3.26}$$

$$x_4 \leq k_4 W_c \tag{3.27}$$

$$x_5 \leq k_5 H_c \tag{3.28}$$

$$x_6 \leq k_6 L_c \tag{3.29}$$

Lithium-ion is the battery technology considered in the baseline case. The energy/weight ratio (ω) for the lithium-ion battery is estimated to be 145 Wh/kg and the energy/size ratio (σ) is 260 Wh/L. Based on these parameters, the battery capacity (F_B) and battery weight ($F_{W,10}$) can be determined in equations (3.30) and (3.31). The cost of manufacturing the battery is estimated by equation (3.32).

$$F_B = 0.01x_4 * 0.01x_5 * 0.01x_6 * \omega/3.7 \tag{3.30}$$

$$F_{W,10} = 0.1x_4 * 0.1x_5 * 0.1x_6 * \omega/\sigma \tag{3.31}$$

$$C_{V,10} = F_B * \ 19.224 \ - \ 8.2696 \tag{3.32}$$

The processor, especially for a Smartphone, is similar to that in a personal computer, carrying out functions, handling input and output tasks, dealing with commands, and controlling signals. Another important component is the camera. The majority of cell phones being sold today include a camera, and its quality is an important consideration for some consumers. Several discrete choices of these two components (x_7, x_8) are considered as shown in table 3.4 and 3.5.

Table 3-4: Discrete choices of processor with related attributes in the cell phone design

	Cost	Weight	Attributes
1	15	1.40 g	0.33 GHz
2	23	1.60 g	0.412 GHz
3	31	1.80 g	0.6 GHz
4	40	2.00 g	0.8 GHz

Table 3-5: Discrete choices of camera with related attributes in the cell phone design

	Cost	Weight	Attributes
1	$ 15	3.00 g	1.92 M
2	$ 20	4.00 g	2 M
3	$ 29	5.00 g	3.2 M
4	$ 40	6.00 g	5 M

The remaining components, like the keyboard, speaker, antenna, and main board, exhibit less variability and regarded here as constants values, as listed in table 3.6. The total manufacturing variable cost and weight is the sum of all components.

Table 3-6: Cost and weight of the remaining components

	Cost	Weight	Attributes
Keyboard	2	3g	-
Speaker	2	3g	-
Antenna	3	3g	-
Main Board	15	15g	-
Others (e.g. power converter)	8	11g	-

At the end-of-life management stage, it is assumed that manufacturers can recover 90% of all their products sold after an average of two years usage time. The average collection and transportation costs per cell phone are assumed to be $6.35 [126].

Based on the earlier discussion, figure 3.2 shows the initial product structure matrix, in which $t_{i,i'}$ represents the disassembly time (unit: s) to separate the component i and component i' for any connected components $C_i, C_{i'}$. A value of $+\infty$ in the disassembly matrix represents that a non-destructive disassembly step is impossible. These include irreversible joints (such as welding or soldering), the presence of components with toxic and dangerous substances, or components with corrosion of deformation, etc.

X	1	2	3	4	5	6	7	8	9	10	11
1	X	40	10	30	10						40
2	40	X					60				
3	10		X				20				
4	30			X			60				
5	10				X		20				
6						X	30				
7		60	20	60	20	30	X	$+\infty$	$+\infty$	10	50
8							$+\infty$	X			
9							$+\infty$		X		
10							10			X	10
11	40						50			10	X

Figure 3-2: Disassembly time in initial product structure matrix

The costs and profits for management of end-of-life modules or components are estimated according to the model in section 2. In this example, all feasible end-of-life components or modules are listed in the first column in table 3.7. A large number of possible module combinations are narrowed down to these options based on the physical connections and potential end-of-life decisions. The whole product (1-11) reuse is not considered in this work.

The estimated recovery profits associated with each end-of-life option are also indicated in this table. To estimate reuse profits, the depreciation factors of different end-of-life modules or components in the cell phone are directly set based on both physical and functional obsolescence, and all modules are assumed to depreciate to the same extent.

Table 3-7: Recovery profits of end-of-life modules

EOL Module	Reuse	Recycling	Disposal
1-11	-∞	-∞	-∞
2-11	-∞	-∞	-∞
3-11	-∞	-∞	-∞
4-11	-∞	-∞	-∞
4-10	-∞	-∞	-∞
4-9	$0.4\sum_{i=4-9} C_{V,i}$-3.61	-0.51*$F_{W,4-9}$	-∞
5-9	$0.3\sum_{i=5-9} C_{V,i}$-3.60	-0.51*$F_{W,5-9}$	-∞
6-9	$0.3\sum_{i=6-9} C_{V,i}$-3.50	-0.45*$F_{W,6-9}$	-∞
5,7-9	$0.3\sum_{i=5,7-9} C_{V,i}$-3.50	-0.45*$F_{W,5,7-9}$	-∞
5-6,8-9	-∞	-0.2*$F_{W,5-6,8-9}$	-∞
5-7,9	-∞	-0.45*$F_{W,5-7,9}$	-∞
5-8	-∞	-0.45*$F_{W,5-8}$	-∞
1	AA: $0.3C_{V,1}$-0.05	0.1*$F_{W,1}$	-0.05$F_{W,1}$
	Plastic: -∞	-0.16*$F_{W,11}$	-∞
2	$0.3C_{V,2}$-2.12	-0.38*$F_{W,2}$	-∞
3	-∞	-0.16$F_{W,2}$	-0.2$F_{W,2}$
4	$0.2C_{V,4}$	-0.2$F_{W,4}$	-∞
5	0.2	-0.32	-0.15
6	0.2	-0.13	-0.15
7	-∞	-0.45*$F_{W,7}$	-∞
8	-∞	-0.45*$F_{W,8}$	-∞
9	-∞	-0.45*$F_{W,9}$	-0.33*$F_{W,9}$
10	-∞	-0.075$F_{W,10}$	-∞
11	AA: $0.3C_{V,11}$-0.05	0.1*$F_{W,11}$	-0.05$F_{W,11}$
	Plastic: -∞	-0.16*$F_{W,11}$	-∞

For material recycling and disposal, the recovery profits and processing costs are evaluated based on material composition and weight ($F_{W,k}$) for the cell phone. A value of -∞ represents an infeasible option. As is shown in table 3.7, several terms describing the end-of-life values are dependent on design variables in the early stage, which is consistent with the earlier discussion.

This optimization problem for the cell phone design is solved using simple Genetic Algorithm (sGA) in Matlab. The optimal simulation results based on the baseline parameter values are shown in table 3.8 and figure 3.3. For the optimal cell phone design, the price is $276.64 with the demand of 186,405 units. The product lifecycle profit is $18.85 million, with $11.88 million from the initial sales and $6.97 million from end-of-life processing.

The optimal design for cell phones derived from our model yields profits from the end-of-life stage, accounting for 37% of the whole lifecycle profits. One critical reason is the reuse of most components in this design. An effective strategy for making early design decisions is to employ high value added components or modules that increase their reusability. Otherwise they tend to become obsolete quickly and not reusable. For example, of the four choices for the processor considered in the model (table 3.4), the one with the attribute 0.8 GHz appeared in the optimal design, has the highest performance, and is more likely to be reused compared to the other three options.

Another issue associated with reusability and end-of-life profits is partial disassembly which can be achieved by using the end-of-life module disassembly matrix presented in this paper. The clustering methods can group components with similar lifetime and end-of-life strategies into one module. The disassembly module in disassembly matrix for the cell phone case study is shown in figure 3.3. Then further disassembly is not required, thus reducing costs. In our model, components 4-9 are projected to be reused as an end-of-life module to avoid further disassembly. Some components must be reused as a module, since further disassembly will physically damage the components. For example, component 8 (Processor) and component 9 (Memory) are impossible to disassemble from component 7 (Main Board) while retaining their functionality.

X	1	2	3	4	5	6	7	8	9	10	11
1	X	40	10	30	10						40
2	40	X					60				
3	10		X				20				
4	30			X			60				
5	10				X		20				
6						X	30				
7		60	20	60	20	30	X	$+\infty$	$+\infty$	10	50
8							$+\infty$	X			
9							$+\infty$		X		
10							10			X	10
11	40						50			10	X

Figure 3-3: Disassembly Module in Disassembly Matrix for the cell phone case study

Table 3-8: The optimal design decisions in the baseline

Component	Design decisions ***x***	Projected EOL modules and decisions
Front Cover	Aluminum Alloy	Reuse
Display	50.72mm *76.08mm	Reuse
Keyboard	--	Disposal
Camera	5 M	Reuse
Speaker	--	
Antenna	--	
Main Board	--	
Processor	0.8 GHz	
Memory	--	
Battery	Lithium-ion, 50.28 mm*7.01mm*60.36mm	Recycle
Back Cover	Aluminum Alloy	Reuse
Product Price & Attributes	Price: $ 276.64 Weight: 142.31 g LCD size: 3.6 inch Battery Capacity: 1.48 Ah Processor Speed: 0.8 GHz Camera: 5 Megapixels	

Further analysis of different design alternatives is conducted to understand their influence on product lifecycle value. The ultimate objective of the analysis is to provide design insights for the manufacturers to improve the cost effectiveness of product life cycle design.

The design variable used for our analysis is the cover material with two options: plastic and aluminum alloy. As discussed earlier, compared with aluminum alloy, plastic is lighter in weight and cheaper in manufacturing cost. Therefore, using plastic for the cover material (other design decisions are kept constant) would yield a cell phone with relatively higher market demand (193,077 units vs. 186,405 units) and higher profit from initial sales ($12.18 million vs. $11.88 million). However, plastic recycling is less profitable, in fact assumed with a negative total profit here, after consideration of all costs involved. So, profits over the whole life cycle, taking into account plastic recycling, is approximately the same as that using aluminum alloy ($18.32 million vs. $18.40 million). In addition, covers made of aluminum alloy are more likely reusable, since metal is more robust to physical damage. So, aluminum alloy is more profitable than plastic over the whole life cycle if reuse is considered, with $18.85 million profit for aluminum alloy compared to $18.32 million for plastic. Note that this analysis does not include consideration of the environmental impacts of recycling or disposal.

Table 3-9: Comparison of the effect of using different materials for cell phone cover

	Plastic	Aluminum Alloy
Demand	193,077	186,405
Initial sales profits	$12.18 M	$ 11.88 M
Profits in whole life cycle if cover is recycled	$ 18.32 M	$ 18.40 M
Profits in whole life cycle if cover is reused	--	$ 18.85 M

Once the optimal solutions have been determined, it is also important to compare the product design options selection under uncertainties in order to investigate the potential benefits. As we discussed earlier, there is frequently a great deal of uncertainties in predicting end-of-life values of these design decisions. For example, Lithium-ion polymer (Li-poly) is the newest battery technology that has been applied in cell phones. However, the Li-ion battery can no longer be fully charged and keep its initial performance after a certain number of charging cycles. So its reuse value is greatly decreased when it reaches the end-of-life stage. Compared to Li-ion battery, the Li-poly battery is more robust to physical damage. In contrast, the returned lithium-polymer batteries can be easily refurbished and reused, giving them higher reuse value. It can also be made lighter and specifically shaped to fit to the devices it will power, as no metal casing is needed. In addition, denser packaging allows it to have an over 20% higher energy density than that of a classic Li-ion battery. However, Lithium polymer based batteries have not yet fully matured and have higher manufacturing costs than Li-ion battery.

In order to make the optimal design decisions with the highest overall expected utility to the manufacturer, it is necessary to evaluate all the options. The uncertainties associated with the product life cycle profits (value function) are largely characterized by a probability distribution function of end-of-values in the future. Future development cannot be predicted for certain. However, it is often possible to estimate the probability by employing prediction methods or expert opinions. In the simulation, we only assume that probability that Li-ion and Li-poly battery can be reused in the end of its lifecycle is 0.2 and 0.5 separately. This probability can be understood as the probability of the battery still working after its first life cycle. If the battery cannot be reused, it has to be recycled due to legislation. In this case study, the manufacturer utility function is estimated as in equation (33) and the value function interval is [0, 30] millions.

$$U(v) = 1.233 - 1.233e^{-0.056*v} \tag{3.33}$$

Table 3.10 shows the effects of using different battery technology: Li-ion and Li-poly. Although the dimensions in the two scenarios are similar, the battery capacity is quite different because of the higher energy density of Li-poly technology. Due to high manufacturing cost, the Li-poly battery product design yields an initial profit of $11.45 million, which is lower than the case when Li-ion battery is used. However, design alternatives need to be considered by permutations over all feasible attribute levels. We listed the possible End-of-Life profits under projected EOL decisions for each case. When the Li-poly battery is used, the optimal product design yields an expected utility of 0.805 in the whole life cycle, which is slightly higher than the case when Li-ion battery (0.803) is used.

Table 3-10: Comparison of effect of using different battery technology

	Li-ion	Li-poly
Dimensions	50.28mm*7.00mm*60.17mm	50.28mm*7.04mm*60.24mm
Battery capacity	1.49 Ah	1.76 Ah
Initial sales profits	$ 11.88 M	$ 11.45 M
Profits under projected EOL decisions	Reuse: $7.56M Recycle: $6.97M	Reuse: $8.15M Recycle: $6.86M
Expected utility	0.803	0.805

3.4 Chapter Conclusions

This paper presented a mathematical model to simultaneously consider initial product sales profits and end-of-life recovery profits. The example illustrated that lifecycle profitability can be optimized when both ends of the product lifecycle are considered during initial product design. As indicated by the methodology proposed in this paper, design decisions in the early stage should not only be based on considerations of initial profit from product sales, but on profit from end-of-life recovery and reuse operations. The model provides design insights that can help manufacturers understand the intricate linkages that exist between the early design decisions and end-of-life strategies. Sensitivity analysis can identify possible design alternatives, so as to further increase profitability.

The challenges for future work are many. Although various approaches have been proposed to integrate the discrete choice model with demand modeling in engineering decision making, demand modeling is still limited in its ability to predict customer behavior with respect to multi-generation products. A design process specifically aimed at upgrading products over multiple lifecycles could also be useful. In addition, the design problem formulation needs to be extended from a single product design to that of a product portfolio. Simultaneously considering multiple market segments could also improve total market share, thus making product recovery more efficient.

3.5 Nomenclature

$\boldsymbol{x}$	The vector of design variables in the early stage
V	The net present value (NPV) of profit over the product lifecycle
c_i	The component *i*
S	The set of components
S_k	The end-of-life module *k*
$\boldsymbol{y}_{\boldsymbol{k},\boldsymbol{l}}$	The end-of-life strategy *l* for module *k*
D	The product demand
P	The product selling price
C_M	The product manufacturing cost
U_{nq}	The utility of customer *n* choose product *q*
V_{nq}	The observed utility of customer *n* choose product *q*
ε_{nq}	The unobserved factors that affect utility but are not considered in V_{nq}
p_s	The logit choice probability
q	The number of products available to customers in the market
$\boldsymbol{\beta}$	The vector of linear coefficients in logit model
$\boldsymbol{z_s}$	The observed product attributes vector
$\boldsymbol{F}$	The product attributes vector
f_F	The functions to capture the relationship between design vector $\boldsymbol{x}$ and product attributes *F*
C_V	The variable costs in the manufacturing process
C_F	The fixed costs in the manufacturing costs
M	The market size
$h(\boldsymbol{x})$	The set of technical equality constraints

$g(\boldsymbol{x})$	The set of technical inequality constraints
γ	Interest rate
t	The average return time (years)
Q	The amount of returned product received by the manufacturers for end-of-life management
R_{EOL}	Recovery profits (can be positive or negative) for end-of-life modules
C_{EOL}	The reprocessing cost for end-of-life modules
C_D	The disassembly costs
C_{CT}	The average collection and transportation costs
$t_{i,i'}$	The disassembly time to separate the component i and component i'
C_L	Unit time labor cost C_L
θ_k	The depreciation factor reflecting customers' perceptions about the remaining value of the module *k*
$C_{V,k}$	The manufacturing cost of module *k*
$C_{k,U}$	The corresponding reuse processing cost
m_p	The total mass (g) of material p in module k;
Pr_p	The projected future unit market price ($/g) of the material *p*
$C_{c,p}$	The projected future unit recycling processing cost of the material *p*.
$C_{D,p}$	Projected future dumping is and landfill cost rate per unit mass of the material *p*
F_W	The weight of the cell phone
F_L	The LCD size of the cell phone
F_B	The battery capacity of the cell phone
F_P	The processor speed of the cell phone
F_C	The camera pixels of the cell phone
v_{min}	The attribute range lower bound
v_{max}	The attribute range upper bound
x_1	Material choice of cover
x_2	The width of display
x_3	The height of display
x_4	The width of battery
x_5	The height of battery
x_6	The length of battery
x_7	The choice of the processor
x_8	The choice of the camera
W_c	The width of the cell phone
L_c	The length of the cell phone
H_c	The height of the cell phone
$F_{W,i}$	The weight of component *i* in the cell phone (*i=1,…,11*)
$C_{V,i}$	The variable manufacturing cost of component i in the cell phone (*i*=1,…,11)
r_C	The weight-to-volume ration of cell phone cover
l_1	The scale factor for the length of the front cover

l_{11}	The scale factor for the length of the back cover
h_1	The scale factor for the height of the front cover
h_{11}	The scale factor for the height of the back cover
k_2	The scale factor for the width of display to the cell phone
k_3	The scale factor for the length of display to the cell phone
k_4	The scale factor for the width of battery to the cell phone
k_5	The scale factor for the height of battery to the cell phone
k_6	The scale factor for the length of battery to the cell phone
ω	The energy/weight ratio for lithium-ion battery
σ	The energy/size ratio for lithium-ion battery

CHAPTER 4 VARYING LIFECYCLE LENGTHS WITHIN A PRODUCT TAKE-BACK PORTFOLIO

4.1 Introduction

4.1.1 Product Take-back Systems

Product stewardship involves everyone - manufacturers, retailers, users, and disposers – taking responsibility to minimize environmental impacts throughout the lifespan of the product. It includes finding effective ways to recapture value and decrease the environmental impacts of already manufactured and used products. Take-back and reuse of such products is an important concept within the product stewardship domain.

Product take-back legislation to close the product lifecycle loop has been enacted in the European Union countries [2] and Japan. The legislation mandates that manufacturing companies extend their responsibility for their products beyond the consumer use phase. Williams et al. [127] provided a summary of take-back legislation for packaging, automobiles and electronic products in several countries, and analyzed the effects of such legislation on design process. The emergence of these existing (and anticipated) take-back laws is a major driving force for manufacturers to incorporate these considerations into product design.

Utilizing recovered products in a remanufacturing operation has potential benefits in addition to compliance with legislation. Energy consumption, material requirements and environmental impacts might be lower than those for newly manufactured products. In addition, “Green” products might appeal to more customers and enhance corporate image. However, remanufacturing systems are more complex than traditional manufacturing systems. Guide [14] analyzed the characteristics and uncertainties that require significant changes in production and control activities for remanufacturing firms. The major sources of uncertainty are in the timing and quantity of returned products and their components. White et al. [128] presented an overview of end-of-life (EOL) management challenges in each stage of the recovery process for rapidly obsolete products such as computers and electronics. It was pointed out that more complete information about product design, quality and timing can improve the end-of-life opportunities.

Long range product planning can help the manufacturer make end-of-life design decisions. Mangun and Thurston [15] developed an EOL decision model where a leasing program (where the manufacturer can control the timing of product take-back) facilitates component reuse, remanufacturing and recycling over multiple but static length lifecycles. This paper deals with the critical problem of fine tuning the lifecycle (both the timing and length) in order to best satisfy different customer needs. In addition, post optimality analyses are performed to gain further insights into redesigning of the product.

4.1.2 Product Lifecycle

Product lifecycle is a collective term for the stages undergone by a product in its lifespan. In general, the stages include material processing, manufacturing, assembly, transportation, product use (usually the longest phase), and end-of-life management. Life Cycle Assessment (LCA) requires estimation of environmental impacts throughout all the stages shown in Figure 4-1. LCA not only informs strategies that would otherwise be developed without consideration of the environment, but also pinpoints critical areas to focus upon in a product's lifecycle. The goal of lifecycle design is to make decisions early during the design process that maximize overall life-cycle value while minimizing cost and environmental impact [15]. When a product reaches the end of one lifecycle, a number of possible recovery options are available: reuse, remanufacture, recycle or disposal, as shown in Figure 4-1. King et al. [11] compared these four alternative strategies to reduce waste within the context of extended producer responsibility. Rose et al. [129] proposed a method to determine feasible strategies based on product characteristics, and developed a web-based application, End-of-Life Design Advisor (ELDA). By understanding end-of-life strategies, redesign improvements can be identified from these results. Gonzalez and Adenso-diaz [113] developed a model to simultaneously determine EOL strategy and disassembly sequence based on product structure. The structure is obtained from its bill of materials (BOM) and the joining geometrical relationship among the components. Other studies have investigated the disassembly process, which plays an important part of end-of-life management. Lambert and Gupta [32] discussed different methods to make a product easy to disassemble and recycle. Behdad et al. [108] presented a model to consider sharing disassembly operations in order to improve the end-of-life strategies for multiple products. Peng and Chuang [104] presented a method for non-destructive selective disassembly planning in a dynamic demanufacturing environment with respect to product maintenance issues.

EOL scenarios can vary depending on the technical characteristics of the returned products. Xing and Belusko [46] proposed the design for upgradability algorithm that can improve the functionality of reused and remanufactured products. The enhanced upgradability can help manufacturers to make long term upgrade plan for multi-generations of a product. Therefore, it is essential to make the optimal decisions not only for one lifecycle but multiple lifecycles together. For example, Dunmade [130] discussed the concept of design for multi-lifecycles and its link with sustainable design, and applied this concept in the agro-industrial sector. Zhou et al. [131] presented a multi-lifecycle product recovery model, optimal retirement planning and design selection methods. The method was illustrated via computer monitor and PC. The results can help manufacturers fully incorporate environmental issues in product design and lifecycle planning.

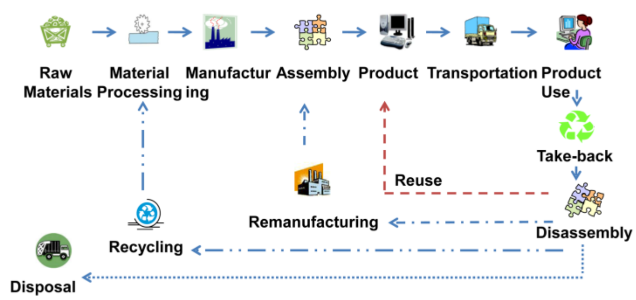


Figure 4-1: Product Life Cycle and End-of-Life Decisions

4.1.3 Research Approach

This chapter uses the life cycle design method which integrates environmental issues into product development by considering all the stages in multiple product life cycles. A multi-objective methodology is applied to the problem of take-back and remanufacturing over multi-lifecycles. The Non-dominated Sorting Genetic Algorithm-II is employed to define the Pareto optimal frontier. Then, normative multiattribute utility analysis is used to evaluate these non-dominated solutions over product attributes.

4.2 Method to Determine Varying Lifecycle Lengths

This section describes a method to determine optimal take-back decisions, including the EOL operations as well as lifecycle lengths for a portfolio of products aimed at different market segments.

4.2.1 Need for Varying Lifecycles

Reducing the amount of disposed material is an important strategy for reducing environmental impact. However, it is often impractical for the whole product to be reused directly due to reliability and technical obsolescence issues. Over multiple lifecycles, decisions to dispose or upgrade decisions need to be made many times. Figure 4.2 (a) and (b) illustrate this concept from the perspective of performance. For a given planning horizon, one can expect the performance to decrease as a function of time. Since the end user imposes a constraint in terms of minimum acceptable performance, shown with the horizontal line in 4.2 (a), the product may become infeasible within the time horizon. This will require the customer to either purchase a new product or upgrade the existing one. Either of these will result in an increase in the performance level, as shown. The upgrade might have to be done multiple times depending on the length of the planning horizon, the minimum acceptable performance level specified by the customer and the rate of decrease in performance. Of course, there are concomitant costs and environmental impacts of upgrade. In practice the scenario can be even more complex. The customer wants to optimize products attributes over the whole planning horizon and over multiple lifecycles. One can choose to do a partial upgrade, allow the product to be upgraded well before it becomes infeasible, and also allow for different lifecycle lengths, as shown in Figure 4.2 (b). This will require understanding of the effect of partial upgrade on cost and environmental impact, in addition to performance. At the same time, reuse/upgrade decisions in one lifecycle will affect those in others. As an example, it might be better to delay an upgrade so that the number of lifecycles can be reduced if this has a positive impact on other attributes and vice versa. The driving forces behind the lifecycle decisions are the customers' willingness to make tradeoffs among attributes.

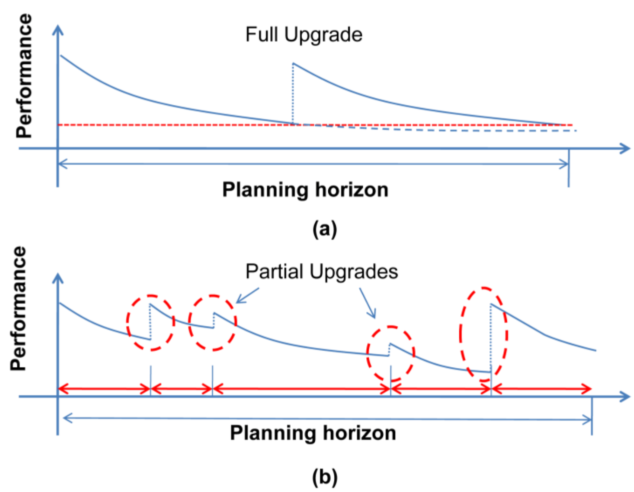


Figure 4-2: The effect of partial and full upgrade on performance within a specified planning horizon

Reliability is used here as a proxy indicator of product performance. It is defined as the probability that a product/component will perform its intended function during a specified period of time under stated conditions. The prediction and control of product reliability play a key role in profitability, especially for products considering component reuse and remanufacturing. For these reused or recycled components, it is necessary to inspect physical reliability at the end-of-life stage to ensure proper quality in the next generation. Various studies have focused on reliability modeling in product remanufacturing and recycling. Shu and Flowers [132] proposed a reliability model to measure the life cycle costs for remanufacturing systems. The model discussed the failure characteristics in series systems when only some parts are replaced. Jiang et al. [133] extended this model to incorporate system population changes.

One issue to consider is that if a component is found to be fully functional at the end of one lifecycle, its physical reliability at the end of the next lifecycle is actually increased. This is because the probability of failure at the end of the second lifecycle is now conditioned on the fact that the component survived the “infant mortality” phase and the first lifecycle. For electronic products, however the perceived performance can be distinct from physical reliability, albeit correlated with time. This is because of continuous technological change and design upgrades inherent to electronic products. As mentioned earlier, since reliability is used only as a proxy for performance, we do not make this change in our calculations of reliability. A monotonic decrease in reliability is maintained and signifies that a component is losing value whether or not it has failed physically.

4.2.2 End-of-life Design Decisions

The four end-of-life recovery options considered here (reuse, remanufacturing, recycling, and disposal) along with the necessary manufacturing operations are shown in Table 4.1. Reuse requires that the recovered component undergoes only minor cleaning and refurbishment. In contrast to the other options, reuse is generally the highest level of product recovery in terms of cost and environmental impact reduction [118]. Components can generally be reused only when they retain their full functionality, while physical and/or technical obsolescence sometimes limit reuse.

The next option is remanufacturing. Lund [134] defined remanufacturing as an industrial manufacturing process in which a worn-out or discarded product is restored to like-new condition. Recovered components may require some rework (such as milling), repair, or replacement of broken or obsolete parts before they can be employed in the next generation product.

Recycling involves activities by which discarded materials are collected, sorted, shredded, and undergoes a reforming process order to prevent the waste of potentially useful materials [135]. The final EOL option is disposal and replacement with a new component in the next lifecycle. Disposing of these components or products without any resource recovery thus represents a waste of the resources and value-added in previous lifecycle. Although many methods of evaluating and improving remanufacturability or recyclability have been proposed [136], [137], [138], many producers are still reluctant to use recycled materials because of uncertain quality or supply standards [139], [140].

Table 4-1: Related operations for end-of-life options

OPERATIONS	Reuse	Remanufactur	Recycling	Disposal
(1) Collection	X	X	X	X
(2) Disassembly		X	X	X
(3) Material Processing			X	X
(4) Manufacturing			X	X
(5) Assembly		X	X	X
(6)Remanufacturing		X		
(7) Recycling			X	
(8) Disposal				X

The four end-of-life design decisions will directly determine the end-of-life processing cost and value, along with the environment impact. The controllable binary (0-1) design decision variable set for EOL options $x_{l,i,j}$ $(j = 1, 2, 3, 4)$ is defined as follows:

$x_{l,i,1}=$ 1 if component i of product in life cycle l is reused, 0 otherwise;

$x_{l,i,2}=$ 1 if component i of product in life cycle l is remanufactured, 0 otherwise;

$x_{l,i,3}=$ 1 if component i of product in life cycle l is recycled, 0 otherwise;

$x_{l,i,4}=$ 1 if component i of product in life cycle l is disposed and replaced with new one, 0 otherwise.

4.2.3 Multi-lifecycle Product Take-back Decision Model

In decision analysis, the attributes are defined as "dimensions of value." The attributes can be viewed as the aspects of a product that either partially or completely address customer needs. For each attribute, customers exhibit a range over which they are willing to consider alternatives, and also a degree of willingness to make tradeoffs among attributes. So the term “attribute”, rather than “objective” is employed, since maximizing or minimizing one attribute is no longer the goal. Rather, maximizing the utility derived from a particular bundle or combination of attribute is the goal. In this model, product price, environmental impact, and product performance (reliability) are the three attributes influencing customers’ choices.

The objective function seeks to minimize a function of product price (P), environmental impact (E), and maximize reliability (R) over multiple lifecycles in the planning horizon:

Objective Function:

$$\min\{P, E, -R\} \tag{4.1}$$

$s.t.$

$$\sum_{j=1}^{4} x_{l,i,j} = 1 \qquad i = 1, \dots, s \tag{4.2}$$

$$\sum_{l=1}^{L} a_l = T \qquad L \in I \tag{4.3}$$

The controllable decision variables include the four possible EOL options $x_{l,i,j}$ for each component in each lifecycle, as well as the length of each lifecycle a_l. The equations (4.2) determine that each component undergoes only one of the four EOL options in each life cycle, where s is the number of components. Equation (4.3) constrains the sum of usage time in the various lifecycles to be equal to the leasing planning horizon (T years), with no time gaps between any two consecutive lifecycles. The number of life cycles (L) is an integer decision variable.

The product price P is the amount of the money that customers are willing to pay for the leasing service (products in all lifecycles). Equation (4.4) indicates that the price is the sum of manufacturing cost C_l and profit Q_l in all lifecycles. The manufacturing cost in each life cycle C_l is considered as the sum of processing costs for each component ($i = 1, \dots, s$) in equation (4.5).

$$P = \sum_{l=1}^{L}(C_l + Q_l) \tag{4.4}$$

$$C_l = \sum_{i=1}^{s} C_{l,i} \tag{4.5}$$

The end-of-life processing cost for each component depends on the end-of-life decision, as determined by the operations ($c_{l,i,n}$) combinations (n=1, …, 8) as required in table 4.1, and shown in equation (4.7-4.10).

$$C_{l,i} = \sum_{j=1}^{4} C_{l,i,j} x_{l,i,j} \tag{4.6}$$

$$C_{l,i,1} = c_{l,i,1} \tag{4.7}$$

$$C_{l,i,2} = \sum_{n=1,2,5,6} c_{l,i,n} \tag{4.8}$$

$$C_{l,i,3} = \sum_{n=1,\dots,5,7} c_{l,i,n} \tag{4.9}$$

$$C_{l,i,4} = \sum_{n=1,\dots,5,8} c_{l,i,n} \tag{4.10}$$

Similarly, the environmental impact E is the sum of environmental impacts in each lifecycle E_l, as shown in equation (4.11). The environmental impact in one life cycle in turn is the sum of environmental impacts for each component, which also depends on EOL decisions, as shown in equation (4.12-4.17).

$$E = \sum_{l=1}^{L} E_l \tag{4.11}$$

$$E_l = \sum_{i=1}^{s} E_{l,i} \tag{4.12}$$

$$E_{l,i} = \sum_{j=1}^{4} E_{l,i,j} x_{l,i,j} \tag{4.13}$$

$$E_{l,i,1} = e_{l,i,1} \tag{4.14}$$

$$E_{l,i,2} = \sum_{n=1,2,5,6} e_{l,i,n} \tag{4.15}$$

$$E_{l,i,3} = \sum_{n=1,\dots,5,7} e_{l,i,n} \tag{4.16}$$

$$E_{l,i,4} = \sum_{n=1,\dots,5,8} e_{l,i,n} \tag{4.17}$$

These impact values are expressed as millipoints units (*mPt*) and estimated from widely used commercial software – SimaPro [141]. SimaPro can analyze and monitor environmental performance of products based on life cycle analysis methods. The software evaluates environmental impact based on the inputs of component materials and operations (energy consumption, transportation, processing, usage, waste treatment and so on), separates them into different categories (greenhouse effect, ozone layer depletion, acidification, eutrophication, heavy metals, carcinogens, winter smog, summer smog, pesticides, energy, and solids) and normalizes them to ecopoints or millipoints (*mPt*) using the "distance-to-target" principle [15], [142]. In this paper, the environmental impact of the manufacturing process, transportation and disposal but not the use phase is considered, since the total planning horizon for each scenario is considered constant.

The component end-of-life age $t_{l,i}$ epends on its age $t_{l-1,i}$ when it enters the present life cycle, decisions made $x_{l,i,j}$ regarding its refurbishment or upgrade, and length of use time a_l in the current life cycle. The function g represents the effects of design decisions $x_{l,i,j}$ and the returned component's age on outgoing component age. For, example, remanufacturing will improve the effective age of a component. Specific assumptions will be made about these effects in the example section.

$$t_{l,i} = g\left(t_{l-1,i}, x_{l,i,j}\right) + a_l \tag{4.18}$$

At the end of a particular lifecycle, the component reliability $R_{l,i}$ is represented by the two parameter (characteristic life θ_i and slope of the Weibull reliability curve b_i) Weibull distribution, as shown in equation (4.19), where only the useful life stage is considered in the model.

$$R_{l,i} = exp\left\{-[\frac{t_{l,i}}{\theta_i}]^{b_i}\right\} \tag{4.19}$$

This information provides input to the failure mode function which estimates overall product reliability at the end of the lifecycle. The end-of-life reliability of the product R_l is a function (f) of the reliability of each component based on product failure mode information, as shown in equation (4.20).

$$R_l = f(R_{l,1}, \ldots, R_{l,s}) \tag{4.20}$$

Then overall reliability is defined as the lowest product reliability (equation (4.21)) in all life cycles as the reliability attribute value R.

$$R = min\{R_l\} \tag{4.21}$$

4.2.4 Non-Dominated Sorting Genetic Algorithm-II (NSGA II)

The component level design decisions are considered in order to control and optimize the product attributes. Evaluating a product comprising 12 components with 4 possible EOL decisions requires consideration of a total number of possible product configurations of 4^{12} for just one life cycle. Evaluating multiple lifecycles increases the complexity even further. For example, more than 10^{72} solutions are possible if each component can be reused, remanufactured, recycled or replaced for ten possible lifecycles. Obviously this is a large number and exhaustive enumeration and comparison of all the solutions is not possible. The heuristics is employed in solving the optimization problem for the set of the three attributes of price, environmental impact, and reliability. It determines the Pareto optimal frontier, a manageable number of non-dominated solutions. The stochastic search methods -- Genetic Algorithms [143] in particular have been successfully employed to solve complex engineering problems involving multiple objectives. A number of multi-objective algorithms have been proposed in the literature [144] and the elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Deb et al. [145] is chosen. The algorithm is efficient in approximating the Pareto frontier which considers attributes separately and does not employ information about customer tradeoff behavior over multiple attributes [146]. The algorithm has found several applications in product design. A mass customization decision making problem is addressed in [146] while an extension to the algorithm is utilized in [142] for reuse decision making. After the Pareto optimal frontier is defined, the utility function is employed to identify the best set of tradeoffs.

4.3 Case Study and Results

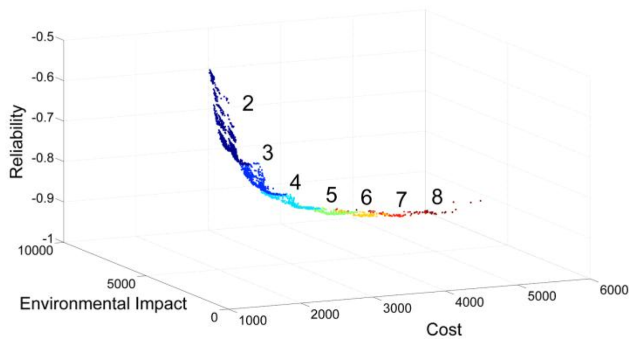
The model presented in here is applied to personal computers; however, the general model structure can be employed for other products as well.

4.3.1 Baseline Results

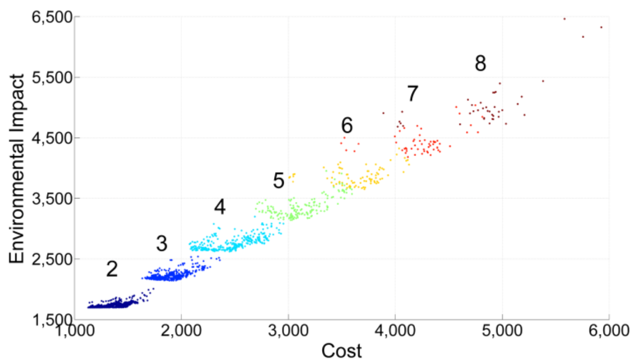
This section presents an example involving personal computers with 12 components for a portfolio of four different market segments. These components are easily separable modules such as the hard drive or the video card. While disassembly of the components into more subcomponents is possible, the results show that consolidating into a smaller number of components (less than 12) does not affect the results significantly.

Failure mode information is required for calculating product reliability, which is based on the component reliability information and component dependencies and criticality. The selection of the critical components is discussed within maximum entropy reliability [147]. Product failure mode occurs when one of the critical components (mother board, hard-drive or video card) fails, or when three of the remaining non-critical components fail together. Recall the discussion in section 2.3 regarding the effects of end-of-life decisions made on component in terms of age. In the simulation, the option of recycling is assumed to recover 90% of the original component value in terms of its age and remanufacturing recovers 50%. The reused component would keep the output age from the previous lifecycle, and disposed component with replacement would be brand new. All component inputs are new at the beginning of the first lifecycle.

The NSGA-II algorithm for this problem is programmed in Matlab. A two-bit string represents the four possible design decisions for each component in a lifecycle, resulting in 24 bits for the product. In addition, one location in the chromosome using real numbers is added to represent the length of the lifecycle. Hence, the total length of the chromosome is 25*(number of life cycles). The population size varies according to the number of lifecycles to account for the increase in problem size. The algorithm searches for solutions from a population set instead of a single point. Two-point crossover is used with probability 0.85; the probability of mutation is fixed at 0.02, and is implemented using the distribution of time-to-next-mutation to gain speedup. These operators can provide adequate mixing of solutions to promote solution diversity and can allow the algorithm to investigate the solution space efficiently, converging to the optimal solutions quickly. Crowding and elitism are also utilized to allow effective evolution in the NSGA-II [145]. The algorithm iteratively searches for better solutions, and each solution is compared to a set of non-dominated solutions. The algorithm finally converges when further improvement in the Pareto frontier is not possible. The Pareto frontier is shown in figure 4.3 (I). In addition to the initial 3-D plot, two dimensional projections (figure 4.3 (II), (III) (IV)) are plotted showing pairs of attributes.



(I)



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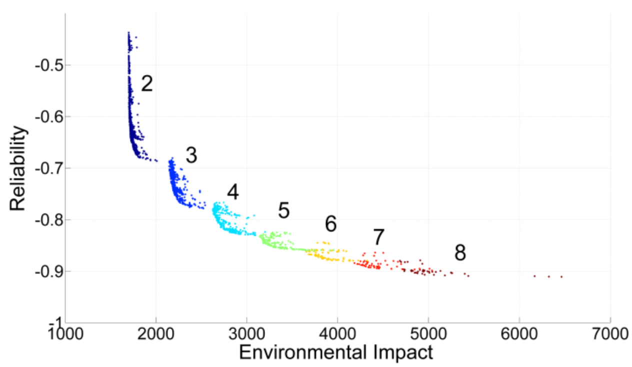
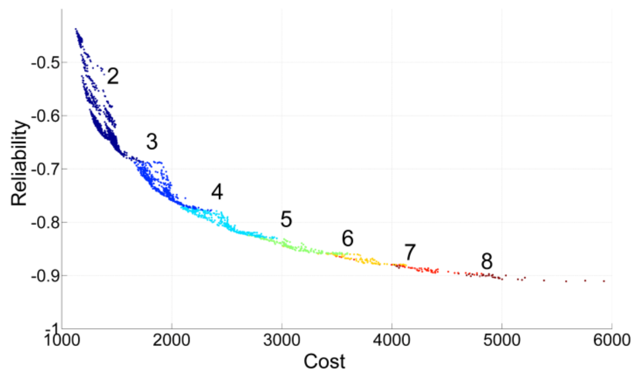


(III)

Figure 4-3: The Pareto Frontier - over price, environmental impact, and reliability and projections



(IV)

Figure 4-3: (cont.)

In general, the values of these attributes increase as the number of lifecycles increases. The data points are represented by different colors indicating the optimal number of lifecycles, ranging from 2 to 8 lifecycles, for these non-dominated solutions. After arriving at the non-dominated solutions on the optimal Pareto frontier, now the question is to determine which solution on the frontier represents the best tradeoffs among price, environmental impact and reliability for each market segment.

Here, a product portfolio composed of four product variants is considered to cover four different market segments: technophile customers, who put more emphasis on the performance of the product and can spend more money to achieve it; utilitarian customers, who want to spend less but buy relatively higher performance product; green customers, who are willing to sacrifice a certain level of performance to reduce the environmental impact; and neutral customers, who do not have significant preferences on one specific attribute. Customer preferences are reflected by two parameters; the ranges over which each segment is willing to consider tradeoffs in each attribute (Table 4.2), and the scaling constants which reflect willingness to make tradeoffs among the attributes, shown in Table 4.3. For price and environmental impact, the values in table 4.2 are averaged over time. Then optimal multi-lifecycle strategies are determined to meet specific customer preferences in each market segment.

Table 4-2: Acceptable attribute range for each market segment and attribute

Market Segment	Price (per year)	Environmental	Reliability
	$(P_{p,min}, P_{p,max})$	$(E_{p,min}, E_{p,max})$	$(R_{p,min}, R_{p,max})$
Technophile	\$600-\$1000	420-1280 mpt	0.84-0.9999
Utilitarian	\$50 - \$600	210-900 mpt	0.60-0.85
Green	\$500-\$1000	105-700 mpt	0.50-0.80
Neutral	\$ 13-\$1068	105-1579 mpt	0.64-0.95

Table 4-3: Scaling constants for each market segment

Market Segment	Price	Environmental	Reliability
Technophile	0.30	0.10	0.80
Utilitarian	0.70	0.35	0.45
Green	0.15	0.85	0.15
Neutral	0.50	0.50	0.50

The non-dominated solutions are evaluated to determine the best combination of price, environmental impact and reliability using utility theory. Various approaches have demonstrated the importance of applying utility theory in engineering decision making [50], [57]. The multiplicative utility function [72] in equation (4.22) is used to evaluate the desirability of attribute tradeoffs. The total planning horizon T is 10 years. $P_{p,min}$ and $P_{p,max}$ define the tolerable range for price, $E_{p,min}$ and $E_{p,max}$ define the tolerable range for environmental impact, and $R_{p,min}$, $R_{p,max}$ define the tolerable range for reliability. The single attribute utility (U_P, U_E, U_R) of each attribute is normalized between 0 and 1 over the acceptable range as shown in equations (4.23) - (4.25).

$$Max\ U_p = \frac{1}{K}\left[\left\{\prod_{a\in\{P,E,R\}}(Kk_aU_a+1)\right\}-1\right] \tag{4.22}$$

$$U_P = \frac{P_{p,max}-P}{P_{p,max}-P_{p,min}} \tag{4.23}$$

$$U_E = \frac{E_{p,max}-E}{E_{p,max}-E_{p,min}} \tag{4.24}$$

$$U_R = \frac{R-R_{p,min}}{R_{p,max}-R_{p,min}} \tag{4.25}$$

Figure 4.3 shows the results of using equation (4.22) to estimate the multiattribute utility of each point on the Pareto optimal frontier for each of the four market segments. The highest utility solutions (optima) are shown in terms of different of number of lifecycles. Multiattribute utility is shown with respect to the optimal number of lifecycles in the 10 year planning horizon. A greater number of lifecycles corresponds to a shorter average lifecycle. Details for the optimal solutions for each market segment are shown in Tables 4.4 – 4.7 in the following.

Ru –Reuse;

Rm—Remanufacturing;

Rc—Recycling;

Rn—Disposal

Table 4-4: Optimal decisions for technophile market segment

Component	Design Decisions							
	LC 1	LC 2	LC 3	LC 4	LC 5	LC 6	LC 7	LC 8
Monitor	Rn	Ru	Ru	Rc	Ru	Rm	Rm	Ru
Floppy Drive	Rn	Rm	Rn	Ru	Rn	Rc	Rn	Rc
Keyboard	Rn	Ru	Rn	Rm	Rm	Rc	Ru	Rm
Hard Drive	Rn	Rn	Rn	Rc	Rn	Rn	Rn	Rc
CD-ROM	Rn	Rc	Rn	Rm	Rc	Rc	Ru	Rn
Mother-board	Rn	Rc	Rc	Rc	Rn	Rc	Rc	Rc
Power Supply	Rn	Rc	Ru	Rc	Rm	Ru	Ru	Ru
Sound Card	Rn	Rc	Rc	Ru	Rc	Rm	Ru	Rc
Video Card	Rn	Rc	Rc	Rn	Rn	Rm	Rc	Rc
Modem	Rn	Ru	Ru	Rn	Rc	Rc	Rm	Ru
Cables	Rn	Rc	Ru	Rc	Ru	Rc	Rm	Ru
Housing	Rn	Rm	Ru	Rc	Ru	Rn	Rc	Rc
Usage time	1.41	1.29	1.25	1.26	1.27	1.12	1.20	1.20
Attributes	P: 5381.1; E: 5436.4;R: 0. 909							
Utility	0.640							

The differences in preferences across the market segments as shown in Tables 4.2 and 4.3 are reflected in differences in optimal take-back profiles for each segment. The technophile segment places more emphasis on reliability, as reflected in a higher reliability cutoff and scaling constant. The result is shown in figure 4.3 (I). Solutions where the number of lifecycles is less than five are infeasible, since they would fall below the acceptable range for reliability. As the number of lifecycles increases, utility increases since the average usage time is decreasing, thereby improving reliability. The optimal multiattribute solution for this market segment is 8 lifecycles over the 10 year planning horizon.

Table 4-5: Optimal decisions for green market segment

Component	Design Decisions	
	LC 1	LC 2
Monitor	Rn	Ru
Floppy Drive	Rn	Rm
Keyboard	Rn	Rm
Hard Drive	Rn	Rc
CD-ROM	Rn	Rm
Motherboard	Rn	Rc
Power Supply	Rn	Ru
Sound Card	Rn	Rc
Video Card	Rn	Rc
Modem	Rn	Rc
Cables	Rn	Rm
Housing	Rn	Ru
Usage time (years)	5.47	4.53
Attributes	*P*: 1521.7; *E*: 1750.6; *R*: 0. 663	
Utility	0.871	

In contrast, figure 4.3 (II) shows that for the green market segment, multiattribute utility increases as the number of lifecycles decrease from 8 to 2 over the 10 year planning horizon. The optimal solution is 2 lifecycles. This is due to the fact that longer lifecycles result in lower overall environmental impact, for which this market segment is willing to sacrifice a certain level of reliability. The results for the other two customer groups (figure 4.3 (III), (IV)) lie between these two extremes as expected. The optimal number of life cycles is 3 and 5 for utilitarian and neutral customers respectively.

Table 4-6: Optimal decisions for utilitarian market segment

Component	Design Decisions		
	LC 1	LC 2	LC 3
Monitor	Rn	Ru	Ru
Floppy Drive	Rn	Ru	Rc
Keyboard	Rn	Rm	Rm
Hard Drive	Rn	Rc	Rc
CD-ROM	Rn	Ru	Rc
Motherboard	Rn	Rc	Rc
Power Supply	Rn	Ru	Ru
Sound Card	Rn	Rc	Ru
Video Card	Rn	Rc	Rc
Modem	Rn	Rc	Ru
Cables	Rn	Ru	Rc
Housing	Rn	Ru	Ru
Usage time (years)	3.92	3.06	3.03
Attributes	*P*: 1986.5; *E*: 2234.6; *R*: 0.758		
Utility	0.837		

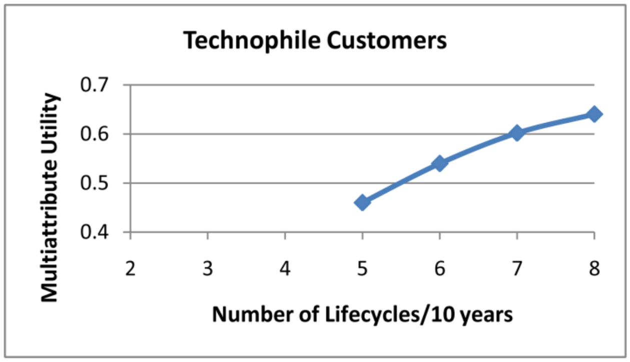
4.3.2 Design Insights

Change of Component Reliability

Analysis of the results can provide important insights into component level design decision problems. From the optimal solutions for the four market segment shown in Tables 4.4 – 4.7, it can be seen that the critical components – hard drive, motherboard and video card – are mostly disposed or recycled (which reduces their effective age to near zero or zero for purposes of improving reliability estimation). Non-critical components are mostly reused or remanufactured in the optimal solution for utilitarian and neutral customers. In the case of green customers, since the optimal number of life cycles is only two, recycling can recover most of the component value without significantly increasing cost. Knowing ahead of time which components will be reused (rather than recycled), the designer can redesign those components in order to further enhance their reusability.

Table 4-7: Optimal decisions for neutral market segment

Component	Design Decisions				
	LC 1	LC 2	LC 3	LC 4	LC 5
Monitor	Rn	Ru	Ru	Ru	Ru
Floppy Drive	Rn	Ru	Rc	Ru	Rc
Keyboard	Rn	Ru	Rm	Rn	Rm
Hard Drive	Rn	Rc	Rn	Rc	Rn
CD-ROM	Rn	Rm	Rc	Rc	Rn
Motherboard	Rn	Rc	Rc	Rc	Rc
Power Supply	Rn	Ru	Ru	Ru	Rm
Sound Card	Rn	Ru	Rn	Ru	Ru
Video Card	Rn	Rc	Rc	Rc	Rc
Modem	Rn	Ru	Ru	Rc	Rc
Cables	Rn	Ru	Ru	Rc	Ru
Housing	Rn	Ru	Rc	Rm	Ru
Usage time(years)	2.28	1.92	1.87	1.90	2.03
Attributes	P: 3124.3; E: 3322.5; R: 0.853				
Utility	0.833				



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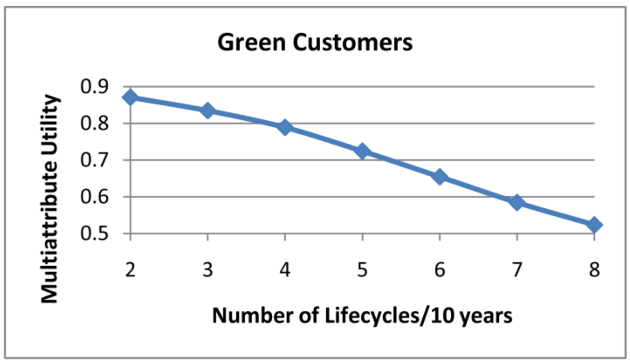

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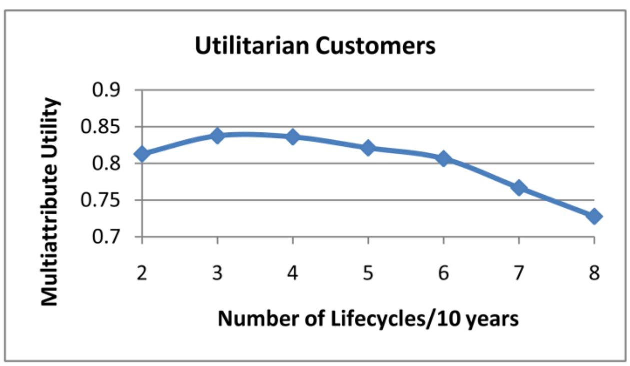
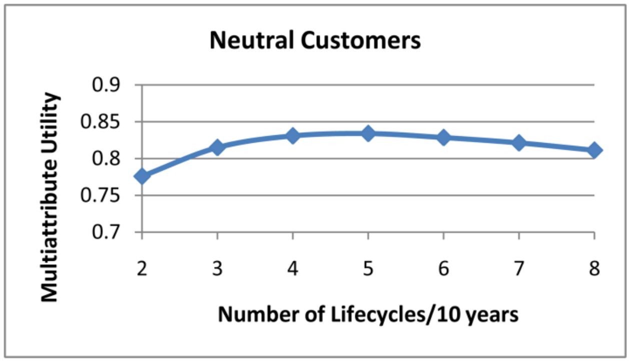


(III)

Figure 4-4: Multiattribute Utility for Non-dominated Solutions with respect to Number of Lifecycles over 10 years for each Market Segment



(IV)

Figure 4-4: (cont.)

An immediate question that might arise in the mind of designers is whether these decisions can be influenced by modifying the reliability functions of components. For the case study, the characteristic life of components is modified to see its effects on the overall utility of the manufacturer. A critical component (hard disk) is considered for the analysis. Simulation results (table 4.8) show that when the characteristic life of the two components is doubled, the utilitarian customers utility would increase from 0.837(U_1) to 0.867(U_2) and three attribute new values are 2017.0, 2268.6, and 0.800.

Table 4-8: The utility comparison for redesign components & parts consolidation

	Technophile	Green	Utilitarian	Neutral
Base	0.640	0.871	0.837	0.833
Redesign	0.711	0.884	0.867	0.853
Parts	0.640	0.870	0.837	0.829

While this result is intuitive if the redesign cost is free, it opens up the avenue to perform a cost-benefit analysis. One can determine how much cost is incurred in increasing the reliability by a given amount. In the case of the hard disk, for example, improving the mechanical elements or the platter material [148] can improve reliability substantially since the electronics are usually considered robust. If the cost-benefit analysis shows that cost per product offsets the utility less than the increase in reliability, redesign can be undertaken.

The isoutility curves of the utilitarian customers are shown in figure 4.5, for a constant environmental impact. The curves can be used to estimate the price increase customers would accept in order to improve reliability attribute. First, the utility of the product is increased from U_1 to U_2 ($U_2 > U_1$) with reliability increased but price. Then a point (U_1') with the same utility as U_1 and the same reliability attribute as in U_2 can be found at the intersection of the isoutility curve U_1 and the vertical line through U_2.The monetary difference between these two prices (as in U_1' and U_2) is the maximum acceptable redesign cost for the reliability change.

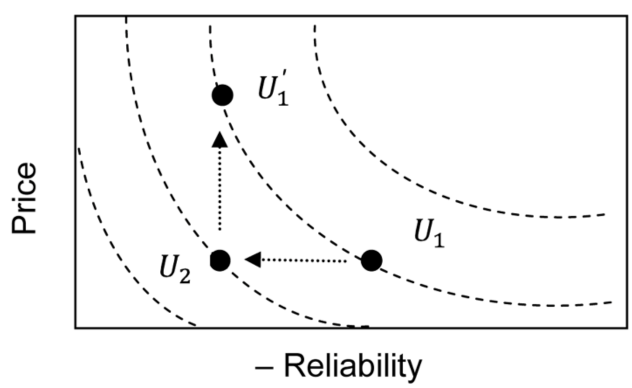


Figure 4-5: Isoutility curves for utilitarian customers

In this case study, to determine this price change, U_1 is fixed at 0.837, and then the new price is calculated to be \$2473 using the multiattribute equation (4.22). Therefore, the manufacturer can spend up to \$2473 – \$2017 = \$456 per product over the planning horizon to improve hard disk reliability through redesign. If the redesign cost is less than the monetary difference, the redesign would improve customers' utility.

Parts Consolidation

Parts consolidation refers to combining of components into one module so that installation into and disassembly from the product is facilitated. In addition, other benefits can also be attributed to parts consolidation such as better tolerances, less inventory and better aesthetics in the case of outer housings, among others. However, parts consolidation removes the freedom that a manufacturer has in terms of decisions they can make while reusing and thus fine tuning the product's performance.

As an example, in the simulation, integrating the sound card, video card and modem is considered to reduce the number of components from 12 to 10 based on the physical proximity and integrability into one module. It means the decisions are the same within each product for these three components. The results (table 4.8) show that the customers' utility would not be significantly influenced by this change, showing that such parts consolidation should be undertaken.

Legislation Constraints

This section explores the impact of varying degrees of take-back legislation. The absence of legislation should improve the manufacturer's utility, since the manufacturer does not have to expend resources on collection or disposal.

Earlier in this paper, take-back legislation was assumed to be imposed on manufacturers to enforce collection of products after they have been used by customers. The following two alternative scenarios are considered: 1) the manufacturer is not required to collect used products, hence the overall cost for manufacturing is decreased; and 2) stricter legislation is enacted and the cost for disposal of some hazardous materials, such as lead, is increased. The environmental impact can be assumed to remain constant in both scenarios as the product is ultimately disposed of in the landfill, even though the decision to do so is made by the customer.

Figure 4.6 shows the results of repeating the analysis under these scenarios. The customer tradeoff behavior is assumed the same as in the baseline case presented earlier. Figure 4.6 shows that the utility changes in the utilitarian market segment under the two different legislative scenarios. Comparing the results to the baseline case, it can be seen that the customers' utility increases slightly when there is no take-back legislation and decreases slightly with more stringent legislation. In addition, the effects of legislation on product take-back would greatly influence the utilitarian customers' utility, since they are more sensitive to the price that they pay for the products.

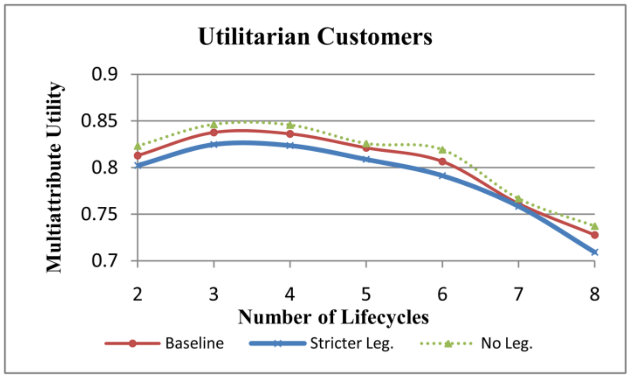


Figure 4-6: Effect of Changes in Legislation for Utilitarian Market Segment

Change in Customer Preference

Sensitivity analysis is also performed to investigate the effect of changes in customer preferences, due either to uncertainties in the initial preference assessment, or to changes in preferences over time. Table 4.9 shows the results. It is anticipated that environmental consciousness will continue to spread throughout the general market. For the neutral customer group, other parameters are kept constant and revise the acceptable environment impact range from [105, 1579] to [105, 900] (per year), reflecting a reduction in the maximum acceptable environmental impact. Comparing the magnitude of utility when different utility functions are employed is not meaningful, so only the resulting optimal decision outcomes are compared. Compared to the baseline case, Table 4.9 shows that the optimal solution calls for fewer lifecycles and fewer new components, in order to decrease the environment impact. Similar results are seen for other market segments.

Table 4-9: Optimal decisions for neutral customers when acceptable environmental impact decreases

Component	Design Decisions			
	LC 1	LC 2	LC 3	LC 4
Monitor	RN	RU	RU	RU
Floppy Drive	RN	RC	RC	RU
Keyboard	RN	RM	RC	RM
Hard Drive	RN	RC	RC	RC
CD-ROM	RN	RN	RC	RC
Motherboard	RN	RC	RC	RC
Power Supply	RN	RU	RU	RU
Sound Card	RN	RU	RN	RC
Video Card	RN	RC	RC	RC
Modem	RN	RC	RU	RC
Cables	RN	RU	RU	RC
Housing	RN	RM	RC	RU
Usage time (years)	2.89	2.39	2.40	2.32
Attributes	*P*: 2605.2; *E*: 2782.3; *R*: 0.82			
Utility	0.803			

4.4 Chapter Conclusions

In this paper, a method is proposed to establish more efficient closed-loop, multiple life cycle product stewardship. A multiple life cycle design decision model was created to help manufacturers identify component level decisions to accommodate flexibility in the number of lifecycles according to different customer needs. The methodology proposed in this paper enables the decision maker to identify a set of non-dominated solutions first and then make optimal decisions based on different customers' tradeoff preferences over multiple attributes.

The challenge for the future work is to more accurately evaluate the reused and remanufactured products' retained functionality, as well as their potential to satisfy dynamically changing customer requirements. Although returned products may still be in good condition in terms of physical reliability, customers often upgrade their products in order to acquire innovative new technology. Hence, it is necessary to consider some performance indicator (and its degradation over time) other than reliability and age. In addition, it is needed to predict accurate cost and environmental impact information for future life cycles in a larger scale product take-back system. This will be challenging as the high variability of remanufacturing and recycling operations will be greatly influenced by as yet unknown technological innovations and changes in customer preferences. Rapid development in data collection, storage and analysis methods can aid in modeling and predicting these manufacturing and marketing trends.

CHAPTER 5 A HIERARCHICAL BAYESIAN METHOD FOR MARKET POSITIONING IN ENVIRONMENTALLY CONSCIOUS DESIGN

5.1 Introduction

Environmentally conscious consumers and environmental protection legislation have been driving manufacturers to design, produce, and dispose products in a more environmentally responsible manner. One of the key issues is how to position environmentally conscious products in the marketplace. Environmentally conscious design eventually needs to make the transition into mainstream design, rather than stay in a high-profile niche application. The assumption that all consumers have the same preferences does not hold in the real marketplace. Heterogeneous customer preferences require analysis of customer choice behavior at the individual level. In addition, individual customer preferences can be clustered into aggregate preferences of different market segments that are latent within the customer base.

In this chapter, a Hierarchical Bayesian method is applied to integrate market considerations, which can be used to measure attributes weights and identify appropriate market segments in which customers value environmentally conscious design. The objective of this paper is to develop an integrative framework that can achieve four aims:

1) Identify market segments for grouping customers who share similar choice behaviors;

2) Select product attributes to be considered in each market segment;

3) Measure the weights of various product attributes;

4) Determine the target market segment in which customers value the environmentally conscious design the most, depending upon the probability of customers adopting the product.

The remainder of this chapter is organized as follows: The Hierarchical Bayesian model framework is presented in section 2 and an automobile design case study is used to demonstrate the proposed approach in section 3 and section 4. We conclude with a discussion of future developments.

5.2 Problem Formulation

Consumer choices are based on bundles of attributes, where each attribute carries a different weight in fulfilling a consumer's needs and requirements. It is necessary to quantify the relationship between a dependent variable (customer choice) and one or more independent variables (product attributes). Based on the choices made by individual-level customers, another key objective of the model is to identify and measure heterogeneous customer preferences in different market segments in which subset groups of customers share similar tradeoff or values.

In the choice-based conjoint analysis, each consumer i ($i = 1, \dots, N$) is provided with sets of product profiles, called choice sets. For each choice set, each customer has to choose a preferred alternative from several alternatives c ($c = 0, 1, \dots, C$) with different combinations of product attributes or attribute levels. The dependent variable Y_{ic}, is a discrete variable that represents a choice or category chosen from the set of mutually exclusive choices or categories.

Customers make choice decisions based on the assumption that they intent to maximize their utilities. While utility maximization is not a controversial assumption, latent utility functions can sometimes not be measured with great certainty. Random utility model, the Multinomial Probit model (MNP), is used here to analyze the discrete choice made by individuals. The latent utility U_{ic} for the alternative c can be decomposed into two parts in equation (5.1):

$$U_{ic} = V_{ic} + \varepsilon_{ic} = \beta_i^T x_{ic} + \varepsilon_{ic} \tag{5.1}$$

Where V_{ic} is the systemic component of utility which is based on observed data and ε_{ic} is the stochastic factor, which takes into account all the variables that have an effect on the utility function. The stochastic part is assumed to have a multivariate normal distribution with a mean vector of zeros and identity covariance matrix. The deterministic utility V_{ic} is expressed as a generalized linear function of unknown heterogeneous coefficients $\beta_i{}'s$ and a vector of observed product attribute x_{ic}, which may include both choice-specific and individual-specific variables, such as price, product performance attributes, and so on. In this case, we assume a multivariate normal distribution on the utilities,

$$U_i|(\beta_i, x_{ic}) \sim N(\beta_i^T x_{ic}, \Sigma) \tag{5.2}$$

Under this situation, the i_{th} individual chooses choice c if and only if

$$Y_i(U_i) = \max\ \{U_{ic}\}\ \forall i \in 1, \dots, N;\ c \in 1, \dots, C \tag{5.3}$$

It is also clear that only utility differences are relevant to model the choice for one alternative. In this case, one alternative (0) is treated as the base alternative and is chosen to work with utility differences between the choices.

$$W_{ic} = U_{ic} - U_{i0} = (x_{ic} - x_{i0})\beta_i + \varepsilon_{ic} - \varepsilon_{ic} \tag{5.4}$$

Under the Multinomial Probit model, the multivariate normal distribution on the difference of latent utility vector $W_i = (W_{i1}, W_{i2}, \dots, W_{i,C})$:

$$Y_i(W_i) = \begin{cases} c & if\ W_{ic} = \max(W_i) > 0 \\ 0 & if\ \max(W_i) < 0 \end{cases} \tag{5.5}$$

Where $W_i = X\beta_i + \epsilon_i$ and ϵ_i is a C×1 vector of disturbance, and Σ is a $C \times C$ positive definite matrix. X is a $C \times P$ matrix of covariates. Y_i equals to 0 means the base alternative is chosen. For Bayesian analysis, it is necessary to specify the prior on the model parameters. In order to avoid the non-identification problem [86], we put a proper prior Inverse Wishart distribution with parameter (v, V) on Σ, which is often used in sampling covariance matrix from a multivariate normal distribution. The priors of β_i and Σ are assumed to be independent.

$$P(\beta_i, \Sigma) = P(\beta_i)P(\Sigma)$$

$$\Sigma \sim InvWishart(v, V) \tag{5.6}$$

In customer latent utility function, β_i is assumed to be $P \times 1$ vector of unknown parameters and P is the number of product attributes. However, different customers for a given type of product or service may have needs that are quite heterogeneous. In this case, $\beta = \{\beta_1, \dots, \beta_n\}$, where β_i is the individual-level coefficients, is used to represent the heterogeneous customer preference. For each individual customer i, the coefficients β_i and ε_i are difficult to estimate due to the large dimensionality of attributes P and small size of observations.

As discussed earlier, market segmentation is an important marketing tool to identify homogenous sub-populations within larger heterogeneous populations. One way to handle these issues is to utilize information of all the respondents and employ Hierarchical Bayesian methods to measure β. If we submitted the individual level parameters to a cluster analysis, the number of K market segments is assumed to represent the different customer preferences in different market segment. A latent variable $G = \{G_1, \dots, G_n\}$ is used to denote the market segment label that each individual customer belongs to, where $G_i = k\ (k = 1, \dots, K)$. Prior probability that market segment label G_i belongs to each market segment is π_k. The Dirichlet distribution $Dir(\boldsymbol{\alpha})$ is used as prior distribution of the multinomial distribution π_k.

In each market segment, the coefficients means $\boldsymbol{\mu} = \{\mu_1, \dots, \mu_K\}$ need to be estimated to indicate the mean of product attribute weights in different market segments, where μ_k is also a $\mathrm{P} \times 1$ vector. In this paper, the prior distribution for β_i is a normal distribution with mean μ_{kp} and variance σ^2. The prior distribution for σ^2 is assumed to be an inverse gamma distribution with parameter α_1 and α_2, which is widely used in Bayesian statistics and served as the conjugate prior of the variance of a normal distribution.

$$\pi(\beta_i|\mu_{kp}, \sigma^2; G_i = k) \sim N(\mu_{kp}, \sigma^2) \tag{5.7}$$

$$\sigma^2 \sim InvGa(\alpha_1, \alpha_2) \tag{5.8}$$

In addition, complex products such as automobiles and electronics often have hundreds of product attributes. It is important to know what features are important to customers in each market segment and how these features should be designed in order to attain an optimum level of satisfaction. Hence, another important design decision is which product attributes to consider for each market segment.

In order to identify the important attributes for each market segment, a latent variable $Z_k = \{Z_{k1}, \dots, Z_{kP}\}$ is introduced to represent whether attribute p should be included in the market segment k. If selected, the prior distribution for μ_{kp} is also a normal distribution with mean 0 and variance τ^2. So we can have

$$\pi(\mu_{kp}|Z_{kp}, \tau^2) = \begin{cases} N(0, \tau^2) & if\ Z_{kp} = 1 \\ 0 & if\ Z_{kp} = 0 \end{cases} \tag{5.9}$$

where $k = 1{:}K$ and $p = 1{:}P$. Similarly, the prior distribution for τ^2 is assumed to be an inverse gamma distribution with parameter $\rho_1\ and\ \rho_2$.

$$\tau^2 \sim InvGa(\rho_1, \rho_2) \tag{5.10}$$

In addition, the likelihood of latent variable Z_{kp} is assumed to be a Bernoulli distribution. It represents that product attribute p needs to be incorporated in market segment k with success probability θ and failure probability $1 - \theta$. θ has the prior beta distribution, which is a family of continuous probability distributions defined on the interval (0, 1) parameterized by two positive shape parameters a and b.

$$\pi\left(Z_{kp}\middle|\theta\right) = Bernoulli(\theta) \tag{5.11}$$

$$\theta \sim beta(a, b) \tag{5.12}$$

The Hierarchical Bayesian analysis is used to capture the uncertainty about the customers' part-worths. The prior distribution is established and posterior probability distributions are derived using Bayesian Theorem, in which the posterior distributions are updated based on the observed choice data. It is computationally very difficult to implement Bayesian approaches in that obtaining the posterior distribution often requires the integration of high-dimensional functions. To estimate various parameters, the Markov Chain Monte Carlo (MCMC) with Gibbs sampling simulation technique was applied, which is particularly useful for exploring posterior probability distributions that arise in Bayesian statistics. The Gibbs samplers are employed for posterior inference over $(U, \beta, \mu, G, Z, \sigma^2, \tau^2, \theta)$. New estimates are updated using an iterative process.

$$P(U, \beta, \mu, G, Z, \sigma^2, \tau^2, \theta | Y)$$
$$\propto P(Y|U) P(U, \beta, \mu, G, Z, \sigma^2, \tau^2, \theta) \tag{5.13}$$

Finally, to succeed in a competitive environment, manufacturers need to estimate the probability that customers are most likely to buy or switch to the environmentally conscious design. In the context of Bayesian analysis, the choice probabilities are computed via the measured product attribute weights in each market segment and product attributes data of the environmental friendly products. This gives the likelihood that the product can be adopted by the customers conditionally on a set of explanatory variables in that market segment. Similarly, manufacturers could explore in relative preferences such as $(U_c > U_{c'} | X; (\mu_k, \Sigma))$.

In this work, predictions of environmentally conscious products given customer preferences in each market segment are very useful for the manufacturers. To get the predictions, we can just to use the estimated parameters as discussed earlier to compute the new choice probabilities, which can be interpreted as the aggregate level as predicted market shares. In this paper, the predicative choice probabilities are calculated via the posterior predicative distribution as in equation (5.14).

$$\Pr(Y' = j | x_C, \mu_k, \Sigma) = \int \Pr(Y' = j | x_C, \mu_k, \Sigma, \mathrm{Y})\, p(\mu_k, \Sigma | \mathrm{Y}) d(\mu_k, \Sigma) \tag{5.14}$$

The limitation of the Multinomial Probit model is that it does not have an expression of the choice probabilities in the closed form when the number of choices is large ($C \geq 4$). It is necessary to use approximation or Monte Carlo simulation techniques.

5.3 Case Study

Although there are some generic tools (such as software WinBugs, MCMCpack, and MNP packages in R) for doing MCMC and Multinomial Probit model, for this non-standard problem, the simulation is programmed in open source software R [149]. The Hierarchical Bayesian model is applied to an automobile data set to conduct inference for the posterior distributions of model parameters.

An automobile design example is used here to demonstrate the proposed approach. Hybrid vehicles offer improved fuel economy and utilize the electrical power of a battery when they can, and traditional gasoline otherwise, so the driver does not sacrifice convenience to gain fuel economy. The automobile manufacturers have invested billions in bringing new hybrid cars to the market in the past few years and are poised to spend more on alternative vehicles. With the Hierarchical Bayesian methods for analyzing consumer choice behaviors, designers can infer consumer demand to make decisions regarding hybrid vehicles. The customer choice data can be analyzed to provide design insights about product positioning of hybrid vehicles.

The automobile data set is obtained from the UC Irvine Machine Learning Repository [150]. It is originally collected from Ward's Automotive Yearbook, Auto manuals, and Insurance collision report, and has been employed in many research areas [151] [152] [153]. The standard data set is easy to access by researchers and enables them to scale and compare data analysis algorithms to very large and complex data sets. This data set consists of 205 instances with 26 attributes. The vehicle attributes include categorical data, integer, and real valued data. The attribute variables and its range are shown in the Table 5-1.

In the original data set, attributes "symboling" and "normalized-losses" are used to represent risk factor symbol associated with its price. A value of +3 indicates that the auto is more risky, and -3 means that it is probably pretty safe. The attribute “symboling” is employed in the simulation but “normalized-loss” is not. In addition, in the vehicle data set used, the vehicle make is not regarded as a product attribute. Although brand or brand loyalty can have a strong impact on customers’ choice of vehicles in real life, it is out of the scope of this work.

Table 5-1: Automobile data set vehicle attributes and its range

Attribute	Range
1.symboling:	-3, -2, -1, 0, 1, 2, 3
2.normalized-losses:	Continuous from 65 to 256
3.make:	alfa-romero, audi, bmw, chevrolet, dodge, honda, isuzu, jaguar, mazda, mercedes-benz, mercury, itsubishi, nissan, peugot, plymouth, porsche, renault, saab, subaru, toyota, volkswagen, Volvo
4.fuel-type:	diesel, gas
5.aspiration:	std , turbo
6.num-of-doors:	four, two
7.body-style:	hardtop, wagon, sedan, hatchback, convertible
8.drive-wheels:	4wd, fwd, rwd
9.engine-location:	front, rear
10.wheel-base:	continuous from 86.6 120.9
11.length:	Continuous from 141.1 to 208.1
12.width:	continuous from 60.3 to 72.3
13.height:	continuous from 47.8 to 59.8
14.curb-weight:	continuous from 1488 to 4066
15.engine-type:	dohc, dohcv, l, ohc, ohcf, ohcv, rotor
16.num-of-cylinders:	eight, five, four, six, three, twelve, two
17.engine-size:	continuous from 61 to 326
18.fuel-system:	1bbl, 2bbl, 4bbl, idi, mfi, mpfi, spdi, spfi
19.bore:	continuous from 2.54 to 3.94
20.stroke:	continuous from 2.07 to 4.17
21.compression-ratio:	continuous from 7 to 23
22.horsepower:	continuous from 48 to 288
23.peak-rpm:	continuous from 4150 to 6600
24.city-mpg:	continuous from 13 to 49
25.highway-mpg:	continuous from 16 to 54
26.price:	continuous from 5118 to 45400

In the case study, we randomly choose 30 vehicles to conduct the discrete choice alternatives, which are shown in the Appendix table.

For the customer choice data, it is best to use survey data and auto sales or market share data from the real market. Here simulation data are used instead. 200 customers' choices were simulated in the conjoint experiments. In order to estimate the parameters in the model more efficiently, multiple choice experiments and observations were conducted. The 30 vehicles are randomly split into 6 groups. The simulation is conducted on each customer, who sequentially views each group and faces a choice within 5 alternatives. A sample of the simulated conjoint experiment data is shown in Table 5-2. In each group, the choice equals to 1 if the alternative is chosen and 0 otherwise.

Table 5-2: Simulated conjoint analysis experiment and customer choice

Customer	Conjoint Experiment	Choice
Customer 1	Vehicle 1	0
	Vehicle 7	1
	Vehicle 10	0
	Vehicle 22	0
	Vehicle 9	0
Customer 1	Vehicle 5	1
	Vehicle 30	0
	Vehicle 19	0
	Vehicle 8	0
	Vehicle 12	0
…	…	…
Customer 200	Vehicle 14	0
	Vehicle 25	1
	Vehicle 23	0
	Vehicle 2	0
	Vehicle 10	0

The first step is the preprocessing of the raw data set for the simulation. The raw data need to be transformed into an acceptable format in a simple text file and imported into R for the simulation.

Attributes such as "fuel-type", "aspiration", "num-of-doors", "body-style", "drive-wheels", "engine-location", "engine-type", and "fuel-system" are examples of a categorical attribute in which the different values have no real numerical relationship with each other. The level of a categorical attribute is recoded into a set of dummy variables. The dummy variable, also called indicator variable, can take the values 0 or 1 to indicate the absence or presence of some categorical effect that may be expected to influence the outcome. For example, we use the dummy variable 0 or 1 for “aspiration” attribute where a vehicle is given a value of 0 if it has "turbo" aspiration or a 1 if it has a "std" aspiration. Dummy variables are useful because they enable us to use a single regression equation to represent multiple groups. This means that we do not need to write out separate equation models for each subgroup.

"Body-style", "engine-type", and "fuel-system" are nominal attributes that have more than two levels. It is necessary to create multiple dummy variables to take the place of the original nominal variable. The number of dummy variables is determined by the number of levels of the original variable. For example, there are five kinds (levels) of body styles in the “body-style” attribute: “hardtop”, “wagon”, “sedan”, “hatchback”, and “convertible”. In this instance, four (5-1=4) dummy variables are created by assigning a variable to each level, which has the value of yes or no (i.e., 1 or 0). Variables, called "body style 1", "body style 2", "body style 3", and "body style 4" are recoded into a value to replace "hardtop", "wagon", "sedan", and "hatchback." If a vehicle has a wagon body style, then "body style 1" would be equal to 0, "body style 2" would be equal to 1, "body style 3" would be equal to 0, and "body style 4" would be equal to 0. If a vehicle has a hatchback body style, then all these four dummy variables are equal to 0. Similarly, attributes “engine type” and “fuel system” are recoded into several dummy variables.

Attributes "symboling" and "num-of-cylinders" are ordinal variables, which are similar to categorical variables. The difference between ordinal and categorical variables is that there is a clear ordering of the ordinal variables. For example, "Num-of-cylinders" can be ordered in terms of number of cylinders, but the size of the difference between categories is inconsistent.

After the data preprocessing, the number of product attributes is 29, which are shown in the first column of Table 5-3. Data transformation such as normalization can improve the accuracy and efficiency of MCMC algorithm. Data normalization transforms data values for different attributes into a uniform set of units or into a uniform scale. In this case, each column is standardized to have zero mean and unit variance.

The model structure discussed above is estimated by the Hierarchical Bayesian methods utilizing the recent advances in Markov Chain Monte Carlo (MCMC) with Gibbs Sampling, which is used as the algorithms for sampling from probability distributions based on constructing a Markov Chain that has the desired distribution as its equilibrium distribution. A key issue in the successful implementation of Gibbs sampler is the number of runs (steps) until the chain approaches stationarity. In addition, the hyper parameters in the models are set to be: $a = 10, b = 5, \alpha_1 = 0.5, \alpha_2 = 2, \rho_1 = 0.5, \rho_2 = 2, \theta = 0.5, v = 200$,

$V = [1, 0.1, 0.2, 0.3;\ 0.1, 1, 0.2, 0.3; 0.2, 0.2, 1, 0.3;\ 0.3, 0.3, 0.3, 1]$.

In the simulation, the length of the burning period is the first 2,000 elements and then one of the various convergence tests is used to assess whether stationarity has indeed been reached. The state of the chain after a large number of steps is then used as a sample of the desired distribution of the posterior parameters. The 1,000 sampling iterations after the burning period are used for the analysis. The likelihood of the MCMC algorithm is shown in Figure 5-1, which shows that the algorithms can achieve the equilibrium distribution in relatively small steps.

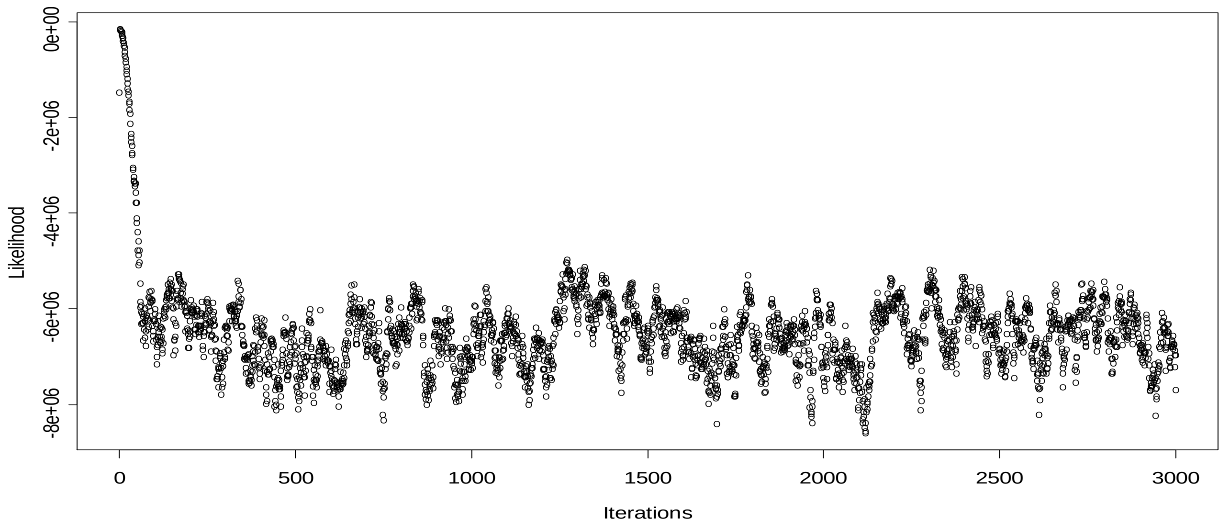


Figure 5-1: The likelihood of MCMC algorithm

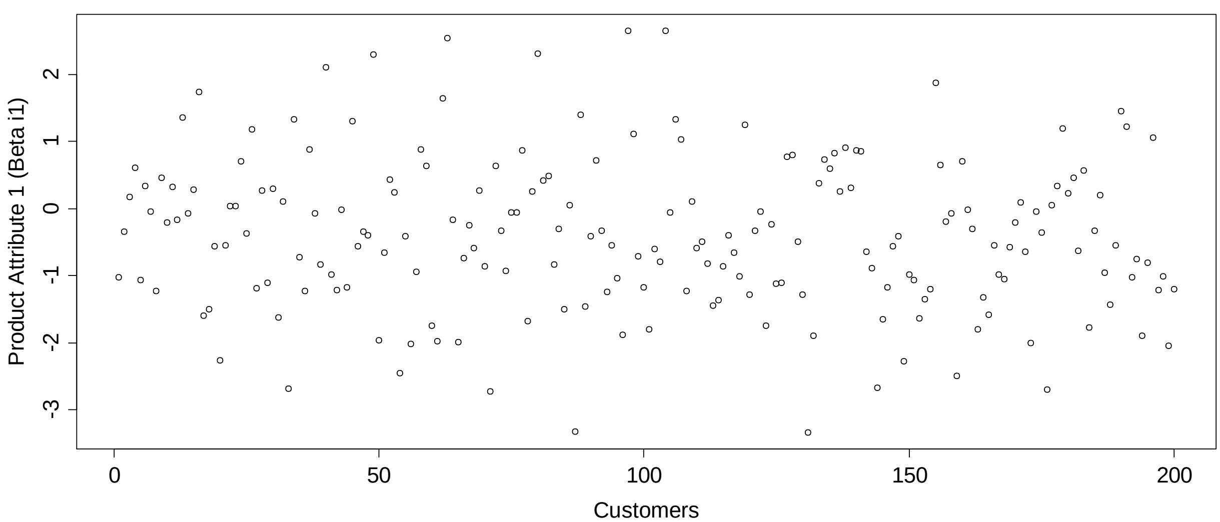


Figure 5-2: The posterior of $\boldsymbol{\beta_i (i = 1, \dots, 200)}$ for product attributes $\mathbf{p = 1, 2, 3}$

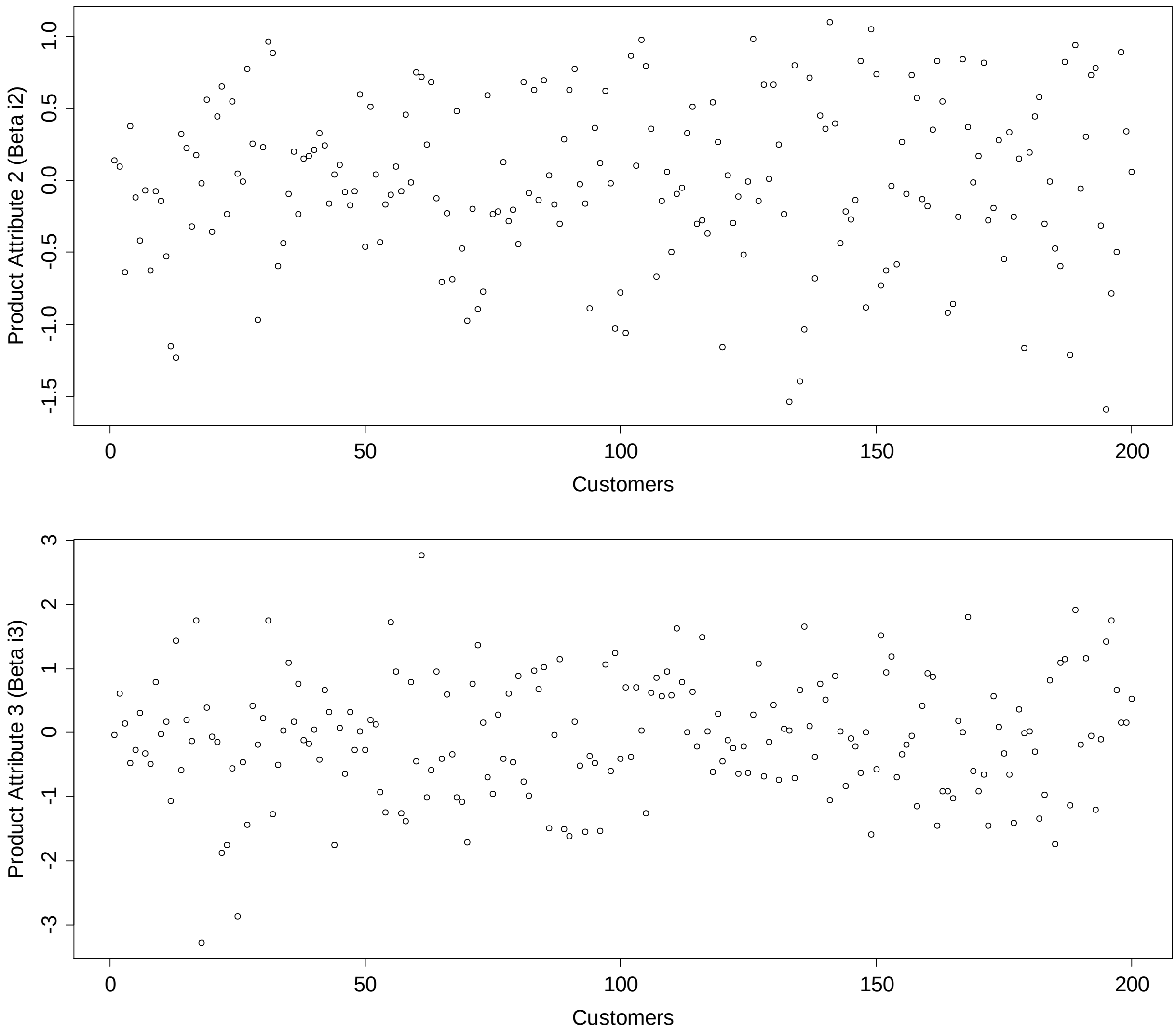


Figure 5-2: (cont.)

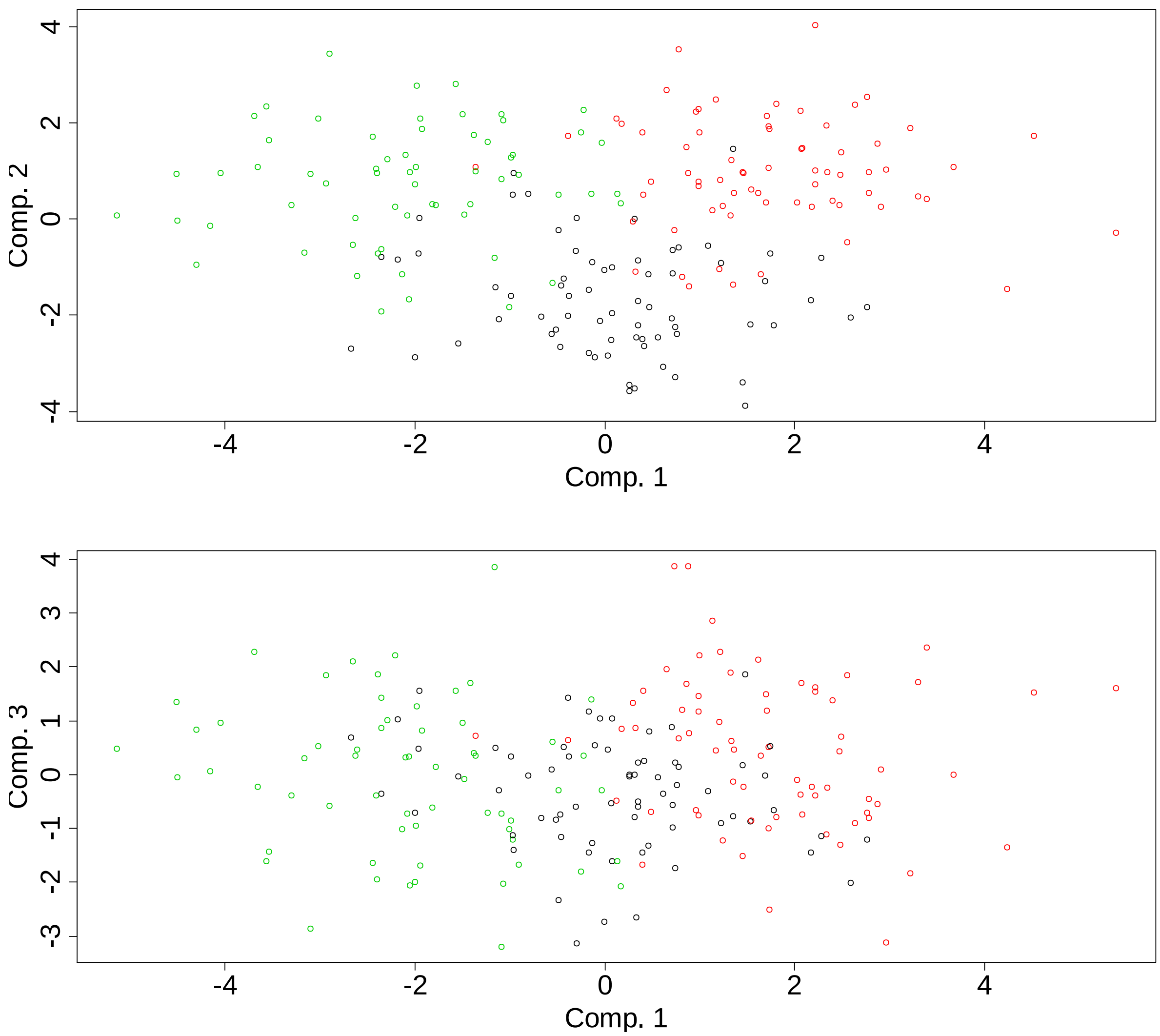


Figure 5-3: Principal components analysis plot of posterior β_i

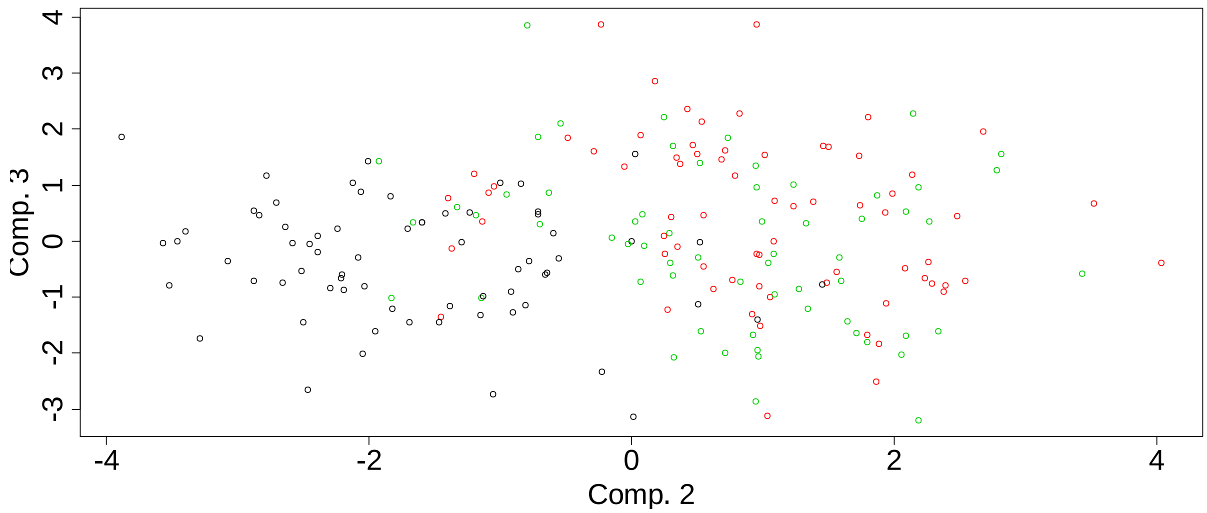


Figure 5-3: (cont.)

The posterior of product attributes weights β_i measures the variations in heterogeneous customer preferences at the individual level. As discussed earlier, β_i is a 29×1 vector of parameters in this case study (29 is the number of product attributes for the automobile data set). We only plot the product attributes $p = 1, 2, 3$ in Figure 5-2.

In order to aggregate heterogeneous customer preferences, we need to identify the number of market segments for grouping customers who share similar choice behaviors. After successful implementation of the algorithm, the results are shown as follows. The number of market segments is a tuning parameter, which can be selected by AIC or BIC. The 200 simulated customers are divided into K=3 groups, including 71 customers in Market Segment 1, 73 customers in Market Segment 2, and 56 in Market Segment 3.

In addition, we performed a principal components analysis of posterior β_i to visualize the clustering. Principle Component Analysis (PCA) transforms the data in the high-dimensional space to a space of fewer dimensions in such a way that the variance of the data in the low-dimensional representation is maximized. In Figure 5-3, the data are projected onto the planes spanned by the three most dominant principal component directions. According to the market segment in which each individual i belongs to (posterior $G_i = k$ $(k = 1, 2, 3)$), red, green, and black were assigned. The estimated product attributes coefficients means $\boldsymbol{\mu} = \{\mu_1, \dots, \mu_K\}$ in each market segment, where μ_k is a 29×1 vector in this case study. The results from the simulation are shown in the Table 5-3.

As shown in Table 5.3, the product attributes are the most significant attributes that will influence customers belonging to a particular niche market making choice decisions. From the simulation results, we can see that customers falling into the Market Segment 1 place more weight on attributes related to safety features when choosing a car. For example, "symboling", which represents risk factor symbol, is -1.228 for MS 1, with a value of +3 indicating that the auto is risky, and -3 meaning that it is probably relatively safe. The coefficient of the attribute "curb-weight" is 0.818, which conforms to the rule of thumb that heavier vehicles offer passengers a greater level of safety. In addition, the customers in this market segment show preference for the "wagon" body style (body-style 2).

Table 5-3: Simulation results of market segments and estimated attribute weights

Attribute	MS 1	MS 2	MS 3
symboling:	-1.228	0	-0.471
fuel-type:	0	0	0
aspiration:	0	0	0
num-of-doors:	0	0	0.414
body-style 1:	0	0	0.596
body-style 2:	0.955	0	0
body-style 3:	0	0	0
body-style 4:	0	0	0
drive-wheels:	0	0	0
wheel-base:	0	0	0
length:	0	0	0.891
width:	0	0	0.636
height:	0	0	0
curb-weight:	0.818	-0.957	0
engine-type 1:	0	0	0
engine-type 2:	0	0	0
engine-type 3:	0	0	0
num-of-cylinders:	0	0	0.949
engine-size:	0	-0.495	0
fuel-system 1:	0	0	0
fuel-system 2:	0	0	0
bore:	0	0	0
stroke:	0	0	0
compression-ratio:	0	0	0
horsepower:	0.375	0	0.929
peak-rpm:	0	0	0
city-mpg:	0.727	1.844	0
highway-mpg:	0	1.032	0
price:	-0.466	-2.014	0

Customers in the market segment 2 express greater regard for fuel efficiency and lower prices. Good fuel economy is considered to be an important attribute of customer choice in this segment, where the coefficients are 1.844 for city-mpg and 1.032 for highway-mpg. In addition, price is one of the most important attributes in this market segment, where the price coefficient is -2.014.

In contrast, the customers in market segment 3 show quite different preferences from those in market segment 1 and 2. Although attributes “symboling” and “price” are weighted in the choice behaviors, customers in this market segment give more weight to the product attributes such as “num-of-cylinders”, “horsepower”, “length” and “width” and so on.

From the results above, we can determine the set of attributes that should be included in the customer’s non-stochastic utility functions in each market segment. It allows the manufacturers to test the effects of changing product attributes or its levels.

Finally, manufacturers may want to predict the choice probabilities or market shares of their environmentally friendly design. The hybrid vehicle data and their attributes need to be gathered from the internet and reports from some of automobile companies. Then we can use equation (5.14) to predict the market performance of hybrid vehicles. The posterior parameters obtained from the simulation can help manufacturers gain insight to predict customer choice decisions for hybrid vehicles. The parameters in the model structure revealed the customer preferences in the market, which can be used to estimate future customer choice patterns. In this case, manufacturers can use the model mentioned above to determine which customer segments the environmentally friendly product should target. Once a market segment has been described, environmentally conscious design and manufacturing need be tailored to address identified segment-specific problems or needs, or to prompt action to be taken.

The calculated results about predicting choice probabilities were not discussed in this case study. There are several reasons: (1) It is important to note that the raw data set for the automobiles is collected from 1980s, which had much lower performance (level of product attribute) even compared to their modern counterparts. The choice probability is expected to be more accurate if data from current market are used; (2) With real sales or survey data, the results generated from the model could be compared to validate the proposed methods and give insights to traditional market segments used by manufacturers; (3) Some product attributes that greatly influence consumer choice between hybrids and conventional cars were not included in the data set, such as "reliability", "battery replacement costs", and so on. Data set for automobiles in the current market need to be collected. A case study using the new data set can give more design insights for the hybrid vehicle manufacturers.

5.4 Chapter Conclusions

This paper presented a Hierarchical Bayesian model for market positioning environmentally friendly products, which enables manufacturers to better understand how the customers respond to environmentally conscious design. Based on the assumption of heterogeneous customer preferences and choice behaviors, the proposed framework can integrate market considerations in product design, which can be used to help designer measure product attribute weights and identify appropriate market segments. A hybrid automobile design example was used to demonstrate the proposed approach.

The existing work will be expanded to include the following issues. First, consumers are becoming more aware of environmental issues, and support the use of eco-labels, reuse or recycling programs. The product attributes including eco-labels, energy efficiency programs, and socio-demographic characteristics need to be incorporated and assessed in the customer choices, in which important attributes that may lead to purchasing environmental friendly products need to be selected. The results can help manufacturers analyze trade-off behaviors.

Second, although various approaches have been proposed to integrate the discrete choice model with demand modeling in marketing or engineering decision making, demand modeling is still limited in its ability to predict customer behavior at the individual level.

Finally, the proposed framework will be integrated with design optimization models, in which environmentally conscious design and manufacturing can be tailored to address identified segment-specific problems or needs. The design problem formulation also needs to be extended from a single product design to that of a product family. Simultaneously considering multiple market segments could also improve total market share, thus making environmentally conscious product more efficient.

5.5 Case Study Data Set

No.	Attributes										
	1	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	3	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	48.8
2	1	gas	turbo	two	hatchback	rwd	front	102.7	178.4	68	54.8
3	3	gas	std	two	hatchback	rwd	front	102.9	183.5	67.7	52
4	0	diesel	turbo	four	sedan	rwd	front	107.9	186.7	68.4	56.7
5	3	gas	std	two	hatchback	rwd	front	91.3	170.7	67.9	49.7
6	2	gas	std	two	convertible	rwd	front	98.4	176.2	65.6	53
7	1	gas	std	four	sedan	fwd	front	105.8	192.7	71.4	55.7
8	0	diesel	turbo	four	sedan	rwd	front	107.9	186.7	68.4	56.7
9	0	gas	turbo	four	sedan	rwd	front	108	186.7	68.3	56
10	3	gas	turbo	two	hatchback	fwd	front	99.1	186.6	66.5	56.1
11	0	diesel	std	four	sedan	rwd	front	104.9	175	66.1	54.4
12	1	gas	std	two	hatchback	rwd	front	99.2	178.5	67.9	49.7
13	2	gas	turbo	four	sedan	fwd	front	99.1	186.6	66.5	56.1
14	1	gas	std	four	wagon	fwd	front	105.8	192.7	71.4	55.7
15	0	gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3
16	0	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3
17	3	gas	std	two	hatchback	rwd	front	94.5	168.9	68.3	50.2
18	-1	diesel	turbo	four	sedan	rwd	front	109.1	188.8	68.9	55.5
19	-1	gas	turbo	four	sedan	rwd	front	109.1	188.8	68.9	55.5
20	1	gas	turbo	four	sedan	fwd	front	105.8	192.7	71.4	55.9
21	-1	diesel	turbo	four	sedan	rwd	front	110	190.9	70.3	56.5
22	-1	diesel	turbo	four	wagon	rwd	front	110	190.9	70.3	58.7
23	0	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7
24	0	gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8
25	3	gas	std	two	hardtop	rwd	rear	89.5	168.9	65	51.6
26	-1	gas	std	four	sedan	rwd	front	115.6	202.6	71.7	56.5
27	0	gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8
28	0	gas	std	two	sedan	rwd	front	102	191.7	70.6	47.8
29	0	gas	std	four	sedan	rwd	front	110	197	70.9	56.3
30	0	gas	std	four	sedan	rwd	front	120.9	208.1	71.7	56.7
31	0	gas	std	two	sedan	rwd	front	103.5	193.8	67.9	53.7
32	1	gas	std	two	hardtop	rwd	front	112	199.2	72	55.4
H1	6	gas*	std	four	hatchback	fwd	front	106.3	170.6	69.7	59.7
H2	4	gas*	std	four	sedan	fwd	front	107.3	182.2	71.7	57.5
H3	5	gas*	std	four	wagon	fwd	front	107.8	178.8	72.2	69.3

No.	Attributes												
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
1	2548	dohc	four	130	mpfi	3.47	2.68	9	111	5000	21	27	16500
2	2910	ohc	four	140	mpfi	3.78	3.12	8	175	5000	19	24	16503
3	2976	dohc	six	171	mpfi	3.27	3.35	9.3	161	5200	20	24	16558
4	3252	l	four	152	idi	3.7	3.52	21	95	4150	28	33	16900
5	3071	ohcv	six	181	mpfi	3.43	3.27	9	160	5200	19	25	17199
6	2975	ohc	four	146	mpfi	3.62	3.5	9.3	116	4800	24	30	17669
7	2844	ohc	five	136	mpfi	3.19	3.4	8.5	110	5500	19	25	17710
8	3252	l	four	152	idi	3.7	3.52	21	95	4150	28	33	17950
9	3130	l	four	134	mpfi	3.61	3.21	7	142	5600	18	24	18150
10	2808	dohc	four	121	mpfi	3.54	3.07	9	160	5500	19	26	18150
11	2700	ohc	four	134	idi	3.43	3.64	22	72	4200	31	39	18344
12	3139	ohcv	six	181	mpfi	3.43	3.27	9	160	5200	19	25	18399
13	2847	dohc	four	121	mpfi	3.54	3.07	9	160	5500	19	26	18620
14	2954	ohc	five	136	mpfi	3.19	3.4	8.5	110	5500	19	25	18920
15	2710	ohc	six	164	mpfi	3.31	3.19	9	121	4250	21	28	20970
16	2765	ohc	six	164	mpfi	3.31	3.19	9	121	4250	21	28	21105
17	2778	ohc	four	151	mpfi	3.94	3.11	9.5	143	5500	19	27	22018
18	3217	ohc	six	145	idi	3.01	3.4	23	106	4800	26	27	22470
19	3062	ohc	four	141	mpfi	3.78	3.15	9.5	114	5400	19	25	22625
20	3086	ohc	five	131	mpfi	3.13	3.4	8.3	140	5500	17	20	23875
21	3515	ohc	five	183	idi	3.58	3.64	22	123	4350	22	25	25552
22	3750	ohc	five	183	idi	3.58	3.64	22	123	4350	22	25	28248
23	3230	ohc	six	209	mpfi	3.62	3.39	8	182	5400	16	22	30760
24	4066	dohc	six	258	mpfi	3.63	4.17	8.1	176	4750	15	19	32250
25	2756	ohcf	six	194	mpfi	3.74	2.9	9.5	207	5900	17	25	32528
26	3740	ohcv	eight	234	mpfi	3.46	3.1	8.3	155	4750	16	18	34184
27	4066	dohc	six	258	mpfi	3.63	4.17	8.1	176	4750	15	19	35550
28	3950	ohcv	twelve	326	mpfi	3.54	2.76	12	262	5000	13	17	36000
29	3505	ohc	six	209	mpfi	3.62	3.39	8	182	5400	15	20	36880
30	3900	ohcv	eight	308	mpfi	3.8	3.35	8	184	4500	14	16	40960
31	3380	ohc	six	209	mpfi	3.62	3.39	8	182	5400	16	22	41315
32	3715	ohcv	eight	304	mpfi	3.8	3.35	8	184	4500	14	16	45400
H1	3042	dohc	four	180	mpfi	3.2	3.5	9	98	5200	42	40	30850
H2	3280	dohc	four	198	mpfi	3.5	3.8	13.8	177	6000	29	29	41875
H3	3641	dohc	eight	205	mpfi	3.6	3.3	9.8	190	5800	25	23	50145

CHAPTER 6 INCORPORATING HETEROGENEOUS CUSTOMER PREFERENCES WITH DIRICHLET PROCESS MIXTURE MODEL FOR PRODUCT POSITIONING IN ENVIRONMENTALLY CONSCIOUS DESIGN

6.1 Introduction

In this section, we proposed a framework for incorporating heterogeneous customer preferences with Dirichlet Process mixture model for product positioning in environmental conscious design. The uncertainty about the functional form of the customer preference distribution can be expressed by using a nonparametric prior. The main goal of this work is to provide models of customers' decision making processes by using Nonparametric Bayesian models. Dirichlet Process mixture model is used in which the number of market segments grows without bound as the amount of sample data grow.

The remainder of this chapter is outlined as follows: The second section present our models in details. In the third section we describe our case study, data set, and preparation for the simulation, and in the fourth section we present our simulation results. The final section offers conclusions and directions for the further research.

6.2 Problem Formulation

In this section, we present the structure of the modeling framework to link heterogeneous customer preferences with environmentally conscious design. It is easy to understand manufacturer behavior by modeling the profit function and assuming profit (V) maximization as shown in equation (6.1).

Objective:

$$max: \; V = D(P - C) = \sum_{i=1}^{N} I(Y_i = J^*)\,(P - C) \tag{6.1}$$

Where D is the demand for the product, P is the selling price, and C is the manufacturing cost. Modeling and forecasting demand for a manufacturer's products, and the resulting revenues accrued is the most critical step. Suppose we have a market in which the number of customers is N. Each consumer i $(i = 1, \ldots, N)$ wants to purchase one of several product alternatives j $(j = 1, \ldots, J)$ in the market. The dependent variable Y_{ij}, is a discrete dependent variable that represents a choice or category chosen from the set of mutually exclusive choices or categories. $I(Y_i = J^*)$ is the indicator function which means customer i choose the product J^* provided by the manufacturer. Therefore, the demand will depend on how many customers select the products provided by the manufacturer. Therefore, it is very important to understand and model customer decision making process in a more accurate way.

Consumer choices are based on bundles of attributes, where each attribute carries a different weight in fulfilling a consumer's needs and requirements. It is necessary to quantify the relationship between a dependent variable (customer choice) and one or more independent variables (product attributes). Suppose we have an individual level customer choices dataset of size n. In the choice-based marketing analysis, each consumer i ($i = 1, \dots, n$) is provided with sets of product profiles, called choice sets or alternatives. For each choice set, each customer has to choose a preferred alternative from several alternatives j ($j = 1, \dots, J$) with different combinations of product attributes or attribute levels. Customers make choice decisions based on the assumption that they intent to maximize their utilities. The discrete outcome variables Y_i, or the decisions made by the customers, is modeled as a function of the latent utility variable U_{ij} as shown in equation (6.2):

$$Y_i = f\left(U_{ij}\right) = \sum_{j=1}^{J} j * I(\max(U_i) = U_{ij}) \qquad (6.2)$$

While utility maximization is not a controversial assumption, latent utility functions can sometimes not be measured with great certainty. Random utility model, the Mixed Logit model (MXL), is used here to analyze the discrete choice made by individuals. Mixed Logit model can avoid the three limitations of standard logit model by “allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time." [111] In Mixed Logit model, the latent utility U_{ij} for the alternative j can be decomposed into several parts as shown in equation (6.3):

$$U_{ij} = \beta_0 + \beta_i^T X_{ij} + \varepsilon_{ij} \qquad (6.3)$$

Where the systemic component of utility $\beta_i^T X_{ij}$ is based on individual customer preference β_i and a vector of observed product characteristics or attributes X_{ij} , and ε_{ij} is the stochastic factor, which takes into account all the variables that have an effect on the utility function. The

X_{ij} matrix may include both choice-specific and individual-specific variables. The stochastic part ε_{ij} is assumed to have an extreme value distribution. β_0 is a vector of alternative specific intercepts, with the intercept for base alternative normalized to zero. With J alternatives, at most $(J-1)$ alternative-specific intercepts can be estimated. The coefficients of $(J-1)$ intercepts are interpreted as relative to alternative base alternative. The deterministic utility is expressed as a generalized linear function of unknown heterogeneous coefficients $\beta_i{}'s$ and a vector of observed product attribute X_{ij}. The dimension of the variables (including β_0 and β_i) is assumed to be p. Then the question is how to find the distribution of heterogeneity for customer decisions. Conditional on β_i, the probability that individual i selects alternative j is simply multinomial logit model:

$$P(j|\,\beta_i) = \frac{e^{\beta_0+\beta_i^T x_{ij}}}{\sum_{j\in J} e^{\beta_0+\beta_i^T x_{ij}}} \tag{6.4}$$

Based on the choices made by individual-level customers, the key objective of the model is to identify and measure heterogeneous customer preferences distributions in different market segments in which subset groups of customers share similar tradeoff or values. Heterogeneity coefficients β_i are typically assumed to be drawn from parametric distributions. However, as we discussed earlier, a Dirichlet Process prior is used to capture the distribution of heterogeneity in customer preferences to avoid the limitations of parametric models. Under this hierarchical framework, it results in a Dirichlet process mixture (DPM) model, which is a mixture model with infinitely many clusters where parameters of each component are drawn from a DP [154]. In this paper, we modeled a set of latent parameters -- individual customer preferences $\{\beta_1, \dots, \beta_n\}$.

$$\beta_i \sim N(\mu_i, \Sigma_i) \tag{6.5}$$

Where μ_i is the mean vector and Σ_i is its precision (inverse covariance matrix). (μ_i, Σ_i) is the set of hyperparameters for components i, which is drawn independently and identically from G. Multiple μ_i, Σ_i can take the same value simultaneously because of the discreteness property of Dirichlet Process.

$$\mu_i, \Sigma_i | G \sim G \tag{6.6}$$

$$G \sim DP(\cdot | G_0, \alpha) \tag{6.7}$$

Where $\alpha > 0$ is a scaling parameter, and G_0 is the base measure. A base normal model is used so that DP mixture model can be interpreted as allowing for a mixture of normal with as many as clusters. The choice of priors for the mean of the normal μ_i is a normal with parameter μ and $(\rho\Sigma_i)^{-1}$ and an Inverse Wishart distribution for the precision Σ_i with parameters ξ and $(\xi\nu)^{-1}$as shown in equation (6.8) and (6.9).

$$\mu_i | \Sigma_i \sim N(\mu, (\rho\Sigma_i)^{-1}) \tag{6.8}$$

$$\Sigma_i \sim IW(\xi, (\xi\nu)^{-1}) \tag{6.9}$$

Where μ, Σ_i , ξ, ν are the hypaerparameters for the mixture components. The hyperparameters prior specifications and posterior distributions for the DP mixtures are not discussed here. The detailed discussion about DP mixture models can be referred to [155] [156]. The DP mixture model is an infinite mixture model, which means a mixture model with a countably infinite number of clusters. The necessary number of clusters used to model data can be inferred from the observed data using Bayesian mixture modeling framework; the actual number of clusters is not explicitly fixed in prior as in finite mixture model. In this case, it is possible to infer the necessary number of clusters (market segments).

6.3 Case Study

To describe the validity of the constructed model, an automobile design case study is used here to demonstrate the proposed approach. The objective of the case study is to analyze consumer choice behaviors in order to infer consumer preferences regarding hybrid vehicles with environmentally conscious design. The customer choice data can be analyzed to provide design insights about product positioning of hybrid vehicles. The automobile data set is relatively easy to access by researchers and enables them to scale and compare results of the data analysis.

Nowadays, automotive manufacturers are moving forward with the development of various kinds alternative fuel vehicles. Hybrid vehicles, commonly known as hybrid electric vehicles, are referred to vehicles that have a combination of an internal combustion engine or one or more electric motor power sources to propel the vehicle. In general, the hybrid vehicles achieve higher fuel economy and lower emissions than conventional internal combustion engine vehicles. It is an effective way to reduce carbon emissions or other man-made emissions of greenhouse gases into the atmosphere, contributing to less harmful impact to the environment. Currently with more and more hybrid vehicles available, it is clear that the hybrid market is no longer in its infancy. A variety of hybrid electric vehicles are currently chosen by customers in the market. From the decisions made by customers among hybrid and conventional vehicles, it is necessary to estimate the heterogeneous customer preferences in order to predict which type of customers would purchase and how to design hybrid vehicles more efficiently in the future.

The raw data in the case study are extracted from the Fuel Economy Guide [157], which is produced by U.S. Environmental Protection Agency (EPA) and U.S. Department of Energy (DOE). The fuel economy data are tested at the Environmental Protection Agency's National Vehicle and Fuel Emissions Laboratory in Ann Arbor, Michigan, and by vehicle manufacturers with oversight by EPA. In addition, other vehicle measurements and specifications are also collected from manufactures' website and commercial websites such as http://www.edmunds.com/.

The original fuel economy data set consists of 1087 instances with more than 60 aspects of automobile design and performance attributes. It includes vehicles of the same production year in 2011. Manufacturers differentiate among their product lines and models in order to target at particular market segment. In this case study, a data frame with 60 instances on 8 variables (Appendix I) is used, in which variables are discussed in greater depth in the following.

1) MSRP, which is the manufacturers' suggested retail price or recommended retail price, measured in U.S. dollars. Incentives and/or Rebates are not considered in this work.

2) MPG, which is estimated based on laboratory testing from the fuel economy report mentioned earlier. All vehicles are tested in the same manner to allow fair comparisons. A city and highway combined estimate is used in the case study.

3) Engine Type. Gasoline and hybrid, referring to hybrid electric vehicles combining an internal combustion engine and one or more electric motors, are considered in the analysis. Although many varieties of alternative fuel cars are available in the market, other fueling options, such as biodiesel, ethanol blends, are not taken into account here.

4) Base Engine. Base engine size or displacement is measured in liters.

5) Horsepower, which is a measure of mechanical power determined by work and its relation to time.

6) Curb Weight, which is the total weight of a vehicle with standard equipment, is measured in pounds.

7) Cargo Capacity, which is used to measure the interior space of a vehicle, with all seats in place, and measured in cubic foot.

8) Body Type. Four body types are considered in the experiments: compact car, midsize car, large car, and SUV.

For the customer choice data, it is best to use survey data and auto sales or market share data from the current market. Here simulation data are used instead. 300 customers' choices are simulated in multiple discrete choice experiments. In each choice experiment, three options are provided for each customer, including two gasoline vehicles and one hybrid vehicle. For each vehicle, the variables discussed earlier are provided. In each experiment, the choice equals to 1 if the alternative is chosen and 0 otherwise. In order to estimate the parameters in the model more efficiently, multiple choice experiments and observations are conducted. In the simulation, each customer is presented as many as 20 choice experiments with different vehicles.

The first step is the preprocessing of the raw data set for the simulation. The raw data need to be transformed into an acceptable format in a simple text file and imported into R for the simulation. “Engine Type” and “Body Type” are nominal attributes that have more than two levels when its values represent categories with no intrinsic ranking. It is necessary to create dummy variables to take the place of the original nominal variable. A dummy indicating that the vehicle is a gasoline or a hybrid is created for “Engine Type”, in which gasoline is the base. The number of dummy variables is determined by the number of levels of the original variable. For the body type, the “compact cars” is taken as the base and other cars are represented in increments in the dummy variables. “Body Type 1”, “Body Type 2”, and “Body Type 3” represent “Midsize cars”, “Large cars” “SUV” separately. In addition, there are two alternative specific intercepts in the utility function due to the number of alternatives is three in the choice experiments. After the data preprocessing, the number of product attributes is 12, which are shown in the first column of Table 6-1.

Table 6-1: Automobile data set vehicle attributes and its range

Attribute	Description
Intercept 1	Continuous number
Intercept 2	Continuous number
MSRP	Continuous number
Cargo Capacity	Continuous number
Curb Weight	Continuous number
Horsepower	Continuous number
Base Engine	Discrete number
MPG	Continuous number
Engine Type	dummy variable: 0/1
Body Type	dummy variables: Body Type 1, Body Type 2, Body Type3

Gibbs sampling is used for inference on the models described in previous discussions. It is a well-known method for generating samples from complex multivariate distributions that is often used as the algorithm for sampling from probability distributions based on constructing Monte Carlo procedures that has the desired distribution as its equilibrium distribution [156]. It is often used to update each variable in turn from its conditional distribution given all other variables in the model. The key of successful implementation of Gibbs sampler is the number of runs steps until the chain approaches stationarity. In addition, data transformation such as normalization is processed to improve the accuracy and efficiency of the MCMC algorithm. In this case, each column is standardized to have zero mean and unit variance.

Various parameters are estimated using Markov Chain Monte Carlo (MCMC), so initial values are set with parameters in all prior distributions. The simulation is programmed in open source software R [149]. We refer to various R packages for coding the Dirichlet Process mixture model and MCMC in the simulation, such as bayesm [158], DPpackage [159], MCMCpack [160].

6.4 Simulation Results

To estimate various parameters, the algorithm is performed in 200,000 runs, updating all parameters and hyperparameters in turn by sampling from the conditional distributions. The results for the case study are extracted from 100,000 MCMC draws after discarding an initial set of 100,000 burn-in draws. A state from the posterior is recorded in every 50 runs. So the final posterior distribution is based on 2000 MCMC draws.

The simulation results give us an adequate understanding of the distribution of consumers' heterogeneous preferences, which will have a direct influence on their purchase decisions. In each MCMC run, the algorithm generates a value for each attribute in the vector of individual customer preference β_i. In this way, we can estimate the posterior density for each attribute. Figure 6-1 shows the posterior marginal distributions of heterogeneity parameter for all the variables (intercepts are omitted) in the model. It clearly shows that the preferences for each attribute $\beta_{i,p}$ vary from customer to customer. The heterogeneity of preference in customers will lead to heterogeneous decisions. From these distributions, it is possible to know how different attributes influence consumers' decisions to purchase a vehicle, in particular when facing hybrids and conventional vehicles simultaneously.

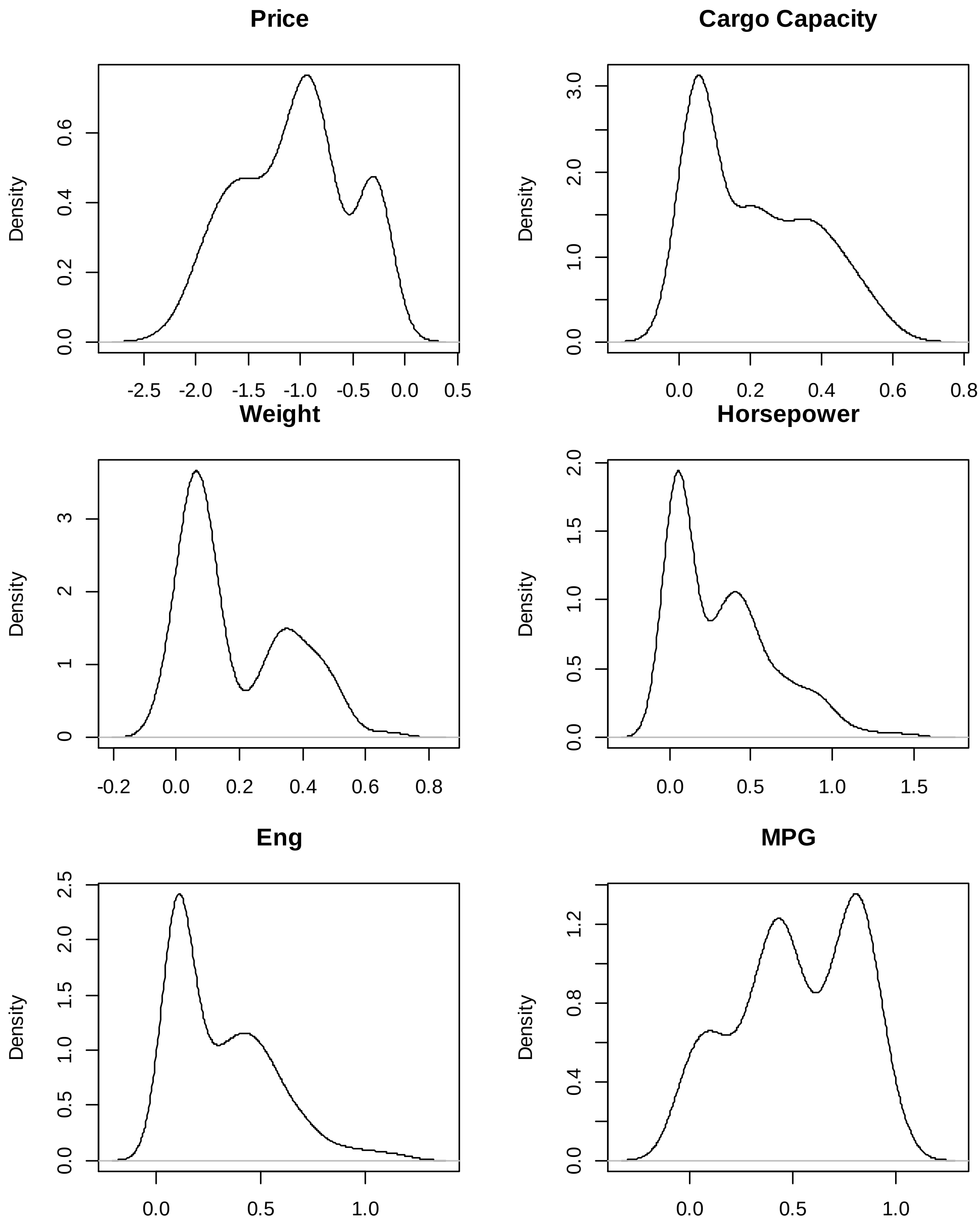


Figure 6-1: Posterior density of heterogeneity parameters

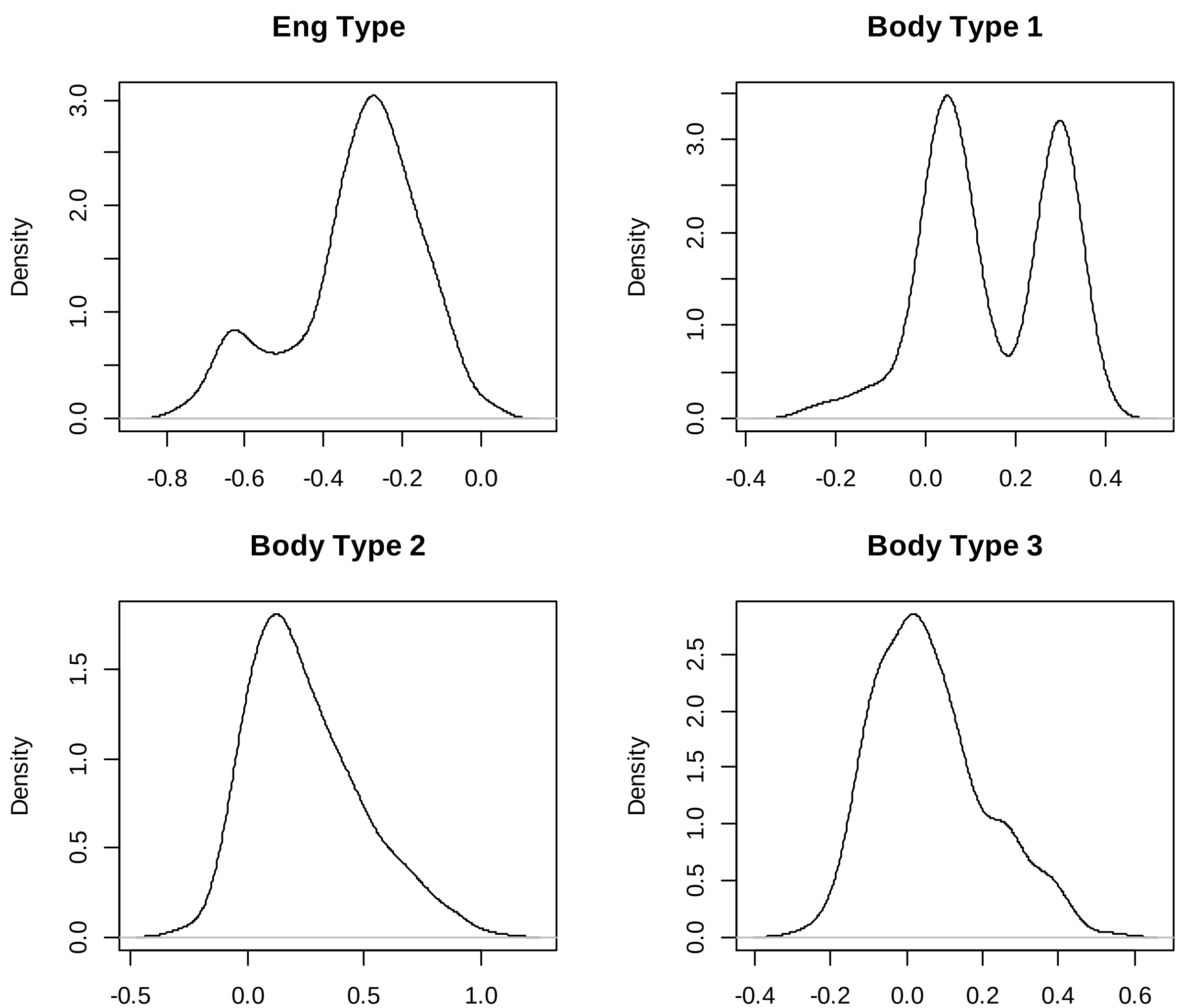


Figure 6-1: (cont.)

In this figure, we can see that most of individual price coefficients are negative, which is as expected, meaning that as the price of a vehicle rises the utility of that customer falls. In a similar way, it is interesting to notice that the "Eng Type" coefficients are negative for most of the customers. In the simulation, a dummy indicating that the vehicle is a gasoline or a hybrid is created for "Engine Type", in which gasoline is the base. It also means a hybrid engine powered vehicle reduces the utility of many customers in the sample set.

In addition, the clustering properties of the Dirichlet Process play important roles in the use of DPs for clustering via DP mixture models. It is applicable to the situations where the number of clusters is not a known priori or is believed to grow without bound as the amount of data grows. The appropriate number of clusters can be determined very quickly. In this paper, the number of clusters can be viewed as the number of market segment. Each individual customer's preferences are viewed as coming from a mixture of probability distributions, each representing a different market segment. In addition, the distribution in each mixture component can be easily determined.

Market segmentation is used to group or segment a collection of customer preferences into subsets or clusters, such that those within each cluster are more closely related to one another than objects assigned to different clusters. Note that larger sample size tends to produce larger number of mixing components. In the simulation, 300 customers are divided into K=3 market segments. The number of customers in each market segment is shown in Table 6-2. Multi-dimensional scaling (MDS) is used in here to make the most useful graphical visualizations. MDS refers to a broad class of procedures that scale objectives based on a reduced set of new variables derived from the original variables. Since the vector of customer preferences is in a multidimensional space, MDS is specifically designed to graphically represent relationships between each individual customer preference. Figure 6-2 shows the MDS plot of customer preferences in the three market segments in the case study. The customer preferences are represented on the plot with the new variables as axes and the relationship on the plot can represent their underlying similarity or dissimilarity. Different colors and legends are used to represent different clusters in the figure.

Table 6-2: Number of customers in each market segment in the mixing

	Market Segment 1	Market Segment 2	Market Segment 3
# customers	125	117	58

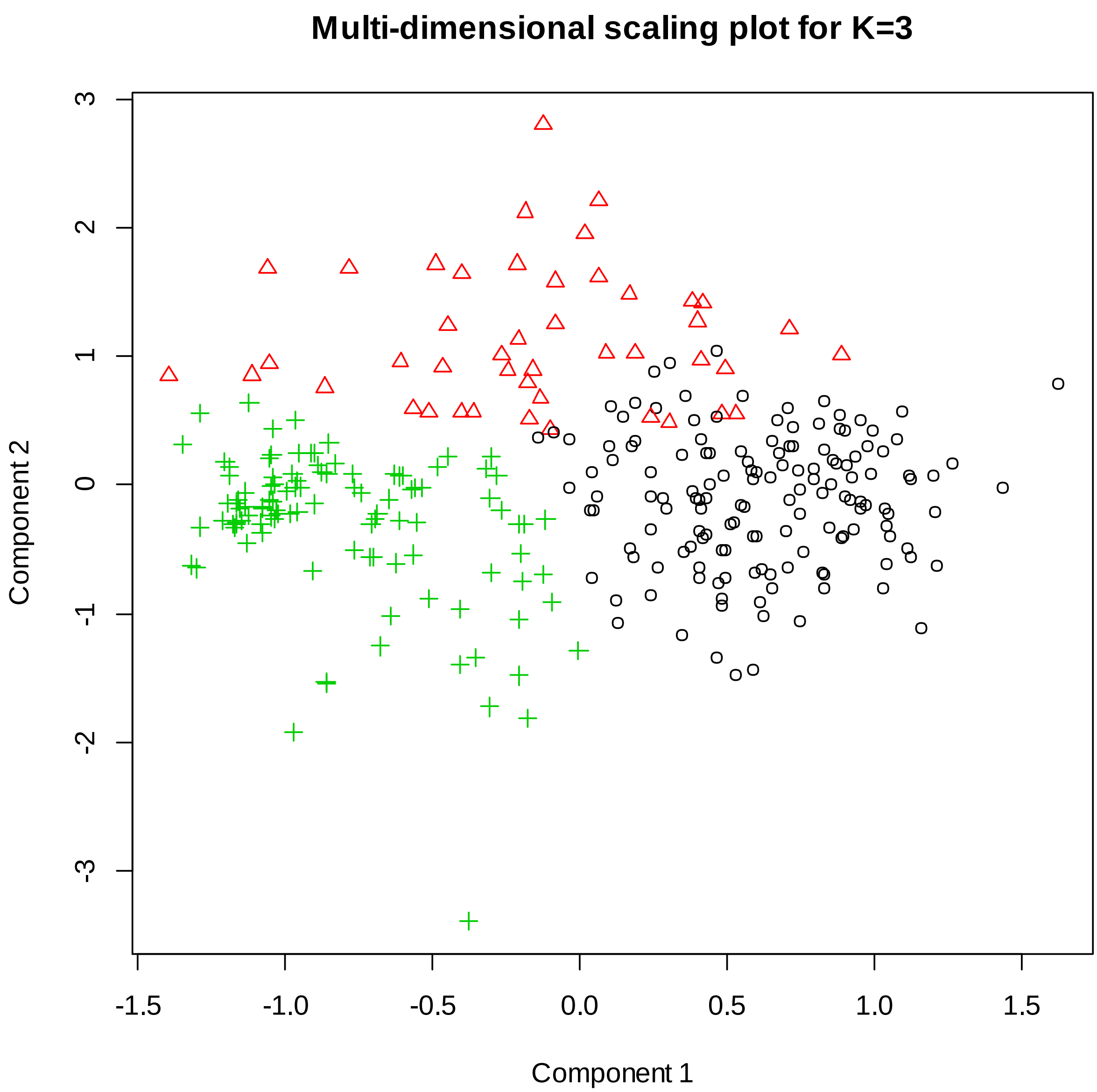


Figure 6-2: Multi-dimensional scaling plot of posterior distribution for the heterogeneous customer preferences

The simulation is operated at the level of individual customers. However, the manufacturers are more interested in some aggregate level measures. Manufacturers need to consider the products or services they provide can conform to the needs of most consumers in a specific market segment.

In addition, the results from the cluster analysis can partition the consumers into different market segments and to better understand the relationships between different groups of consumers/potential customers for product positioning. The posterior means of the parameter estimates over each market segments are presented in Table 6-3. The intercepts in the utility functions are omitted in the table. Due to the simulated choice data in the case study, we cannot use the current market sales data to validate the model and give much design insights for the manufacturers.

Table 6-3: Means of parameter estimates in each market segment

Attributes	MS1	MS2	MS3
MSRP	-1.573	-0.998	-0.604
Cargo Capacity	0.052	0.348	0.301
Curb Weight	0.051	0.331	0.257
Horsepower	0.047	0.346	0.577
Base Engine	0.102	0.371	0.483
MPG	0.807	0.459	0.275
Engine Type	-0.197	-0.298	-0.428
Body Type 1	0.299	0.078	0.03
Body Type 2	0.084	0.336	0.372
Body Type 3	0.003	0.012	0.138

With the above aggregated or clustering results, it is possible to explore the purchasing probability of different vehicles in each market segment. The purchasing probability is treated as the estimated market share for specific vehicle models. Then manufacturers can create different product variants for each segment, each intended to address the average customer need in that segment. We will use the mixed logit model for prediction of market shares. We understand that the customer decisions for purchasing a hybrid vehicle are dependent on many factors in real life, such as state and federal incentives, gas prices, brand, consumer demographics, and so on. Here we just show how the methodology can be applied in this case study. For each market segment, we randomly select multiple vehicles from the data set. We only keep one hybrid vehicle in each market segment. The simulation results are provided in Table 6-4. The market shares of each vehicle in each market segment are listed in the table. For example, the average probability of choosing the hybrid vehicle "Fusion hybrid" in market segment 1 is 0.085. It means it captures a market share of 8.5% in market segment 1.

We estimate the model with the existing vehicles on the market to show the methodology. The manufacturers can tune the design attributes to calculate probabilities with new design. For example, suppose a new hybrid technology is developed that provides higher fuel economy, but the new technology costs more. Using the above methodology, it is possible to calculate the probability and predict the market share (i.e., the average probability in each market segment) for the new technology.

Table 6-4: Market share prediction in different market segments

Models	Market Share in MS1	Models	Market Share in MS2	Models	Market Share in MS3
YARIS	10.06%	MDX	12.92%	ENCLAVE	10.54%
VERSA	9.95%	TOWN	8.14%	AVALON	10.04%
ACCENT	9.01%	GLK350	7.99%	RX450h	9.84%
FUSIONHYBRID	**8.50%**	TIGUAN	7.41%	TRAVERSE	8.77%
CT200h	6.88%	LANCER	7.21%	MDX	8.15%
CIVIC	6.31%	A4	6.42%	DTS	7.62%
COROLLA	6.09%	300	6.19%	**ML450HYBRID**	**5.97%**
FOCUS	5.82%	AZERA	5.59%	TIGUAN	5.75%
ALTIMA	5.17%	RX450h	5.59%	PILOT	4.82%
SONATA	5.06%	AVALON	4.62%	HIGHLANDER	4.64%
CRUZE	4.96%	**S400HYBRID**	**4.58%**	GLK350	4.33%
CAMRY	4.91%	MALIBU	4.54%	TAURUS	4.31%
MALIBU	4.43%	C300	4.21%	TL	2.94%
ACCORD	3.80%	FUSION	3.91%	CC	2.71%
CR-V	3.24%	PILOT	3.83%	E350	2.04%
SANTAFE	3.15%	ENCLAVE	3.67%	CT200h	1.62%
LANCER	2.67%	328i	3.19%	TOUAREG	1.32%

6.5 Chapter Conclusions

This paper presented a framework for incorporating heterogeneous customer preferences with Dirichlet Process mixture model for product positioning in environmental conscious design. With increased environmentally conscious from governments and customers, it would present great challenges for manufacturers to design the products to improve their environmental performance. However, in order to achieve profit objectives, the heterogeneous customer preferences need to be estimated before manufacturers can make optimal design decisions. We formulate the mathematical model in a Nonparametric Bayesian framework and an automobile design example was used to demonstrate the proposed approach.

The existing work will be expanded to for the further research. First, in this paper, the normal base distribution in the Dirichlet Process is assumed. In many situations, however, it may not be an appropriate choice for the customer preference heterogeneity. Transformations of normal can be used to obtain other distributions. In addition, Hierarchical Dirichlet Processes will be used for groups of data, where each observation within a group is a draw from a mixture model, and share mixture components between groups [161].

Finally, the proposed framework will be integrated with design optimization models, in which environmentally conscious design and manufacturing can be tailored by balancing the product attributes in different market segments. In addition, the design problem formulation needs to be extended from a single product design to that of a product family design. Simultaneously considering multiple market segments could also improve total market share and profits.

6.6 Case Study Data Set

Manufacturer	Model	Price	Cargo Capacity	Weight	Horsepower	Eng	MPG	Eng Type	Body Type
Hyundai	ACCENT	13695	12.4	2365	110	1.6	40.21	gasoline	Compact Cars
Audi	A6	45200	15.9	3858	265	3.2	30.36	gasoline	Midsize Cars
Toyota	HS 250h	36330	12.1	3682	187	2.4	47.27	hybrid	Compact Cars
Toyota	YARIS	13715	12.9	2313	106	1.5	41.88	gasoline	Compact Cars
Hyundai	SONATA	20395	16.4	3161	190	2.4	35.30	gasoline	Large Cars
FOMOCO	MKZ HYBRID FWD	34645	11.8	3752	191	2.5	54.18	hybrid	Midsize Cars
Mitsubishi	LANCER	16695	12.3	2922	148	2.0	26.31	gasoline	Compact Cars
GM	IMPALA	24495	18.6	3555	211	3.5	29.64	gasoline	Large Cars
FOMOCO	ESCAPE HYBRID FWD	30570	27.8	3669	177	2.5	44.14	hybrid	SUV
FOMOCO	FOCUS FWD	17270	13.8	2623	140	2.0	37.55	gasoline	Compact Cars
FOMOCO	TAURUS FWD	25555	20.1	4015	263	3.5	27.78	gasoline	Large Cars
Porsche	Cayenne S Hybrid	67700	20.5	4938	380	3.0	28.15	hybrid	SUV
Toyota	COROLLA	17600	12.3	2734	132	1.8	38.95	gasoline	Compact Cars
Volkswagen	TOUAREG	44450	32.1	4711	280	3.6	24.96	gasoline	SUV
FOMOCO	FUSION HYBRID FWD	28600	11.8	3720	156	2.5	54.18	hybrid	Midsize Cars
Honda	CIVIC	17755	12.0	2687	140	1.8	39.61	gasoline	Compact Cars
Mercedes-Benz	E 350	49400	15.9	3825	268	3.5	25.34	gasoline	Midsize Cars
Nissan	ALTIMA HYBRID	26800	10.1	3470	198	2.5	46.71	hybrid	Midsize Cars
GM	CRUZE	18425	15.4	3102	138	1.4	37.17	gasoline	Compact Cars
Volkswagen	CC	28200	13.0	3300	200	2.0	32.37	gasoline	Compact Cars
Toyota	CT 200h	29120	14.3	3130	134	1.8	57.50	hybrid	Compact Cars
Audi	A4	32300	12.0	3527	211	2.0	34.12	gasoline	Compact Cars
Honda	ACCORD 4DR SEDAN	23180	14.7	3287	177	2.4	35.01	gasoline	Large Cars

Toyota	GS 450h	58950	10.3	4134	340	3.5	30.82	hybrid	Compact Cars
Mercedes-Benz	C 300	33900	12.4	3590	228	3.0	27.28	gasoline	Compact Cars
Nissan	ALTIMA	22430	15.3	3193	175	2.5	35.25	gasoline	Midsize Cars
Hyundai	SONATA HYBRID	25795	10.7	3483	206	2.4	52.18	hybrid	Midsize Cars
BMW	328i	34600	12.0	3362	230	3.0	28.54	gasoline	Compact Cars
Nissan	VERSA	14100	13.8	2671	122	1.8	35.87	gasoline	Midsize Cars
Honda	CIVIC HYBRID	23950	10.4	2877	110	1.3	58.84	hybrid	Compact Cars
Hyundai	ELANTRA	14945	14.8	2522	148	1.8	44.37	gasoline	Midsize Cars
Toyota	CAMRY	21650	15.0	3263	169	2.5	33.62	gasoline	Midsize Cars
Toyota	CAMRY HYBRID	27050	10.6	3680	187	2.4	45.94	hybrid	Midsize Cars
FOMOCO	FUSION FWD	21850	16.5	3285	175	2.5	34.86	gasoline	Midsize Cars
Honda	TL 2WD	35305	13.1	3721	280	3.5	27.35	gasoline	Midsize Cars
Toyota	PRIUS	27320	21.6	3042	134	1.8	70.78	hybrid	Midsize Cars
GM	MALIBU	21975	15.1	3415	169	2.4	34.01	gasoline	Midsize Cars
Hyundai	AZERA	25495	16.6	3576	160	3.3	29.48	gasoline	Large Cars
Honda	INSIGHT	19900	15.9	2727	98	1.3	57.28	hybrid	Compact Cars
Chrysler	300	27170	16.3	3961	292	3.6	27.37	gasoline	Large Cars
Toyota	AVALON	33195	14.4	3572	268	3.5	29.98	gasoline	Large Cars
Volkswagen	Touareg Hybrid	60565	32.1	5315	380	3.0	28.20	hybrid	SUV
FOMOCO	TOWN CAR FFV	47225	21.0	4345	239	4.6	24.12	gasoline	Large Cars
Hyundai	SANTA FE 2WD	21845	34.2	3688	175	2.4	29.87	gasoline	SUV
BMW	ActiveHybrid 7	102300	13.0	4795	455	4.4	25.58	hybrid	Large Cars
GM	DTS	46680	18.8	4009	275	4.6	23.18	gasoline	Large Cars
Honda	CR-V 2WD	22595	35.7	3386	180	2.4	31.25	gasoline	SUV
Toyota	HIGHLANDER HYBRID 4WD	38140	27.5	4641	280	3.5	38.69	hybrid	SUV
Volkswagen	TIGUAN	23720	23.8	3433	200	2.0	28.10	gasoline	SUV
Honda	PILOT 2WD	28320	28.0	4319	250	3.5	24.50	gasoline	SUV

Mercedes-Benz	S400 HYBRID	91000	16.4	4474	295	3.5	27.50	hybrid	Large Cars
GM	TRAVERSE FWD	29370	24.4	4790	281	3.6	24.79	gasoline	SUV
Toyota	HIGHLANDER 4WD	32695	27.5	3946	187	3.5	24.42	gasoline	SUV
Mercedes-Benz	ML450 HYBRID 4MATIC	55790	29.4	5227	335	3.5	29.59	hybrid	SUV
Mercedes-Benz	GLK 350	35500	23.3	3979	268	3.5	23.88	gasoline	SUV
GM	ENCLAVE FWD	35865	23.3	4780	288	3.6	24.79	gasoline	SUV
GM	C1500 TAHOE 2WD HYBRID	51145	16.9	5629	332	6.0	28.54	hybrid	SUV
Honda	MDX 4WD	42930	35.5	4550	300	3.5	23.01	gasoline	SUV
Mercedes-Benz	ML 350	46490	29.4	4630	268	3.5	22.55	gasoline	SUV
Toyota	RX 450h AWD	44735	40.0	4520	295	3.5	38.57	hybrid	SUV

CHAPTER 7 A MARKET DRIVEN OPTIMAL UPGRADING DECISION MAKING APPROACH FOR REMANUFACTURED PRODUCTS IN PRODUCT LIFECYCLE DESIGN

7.1 Introduction

While the practical applications may vary, in general, the goal of environmentally conscious technologies is to apply sustainable design principles and use low environmental impact materials and high energy efficiency products that can be reused or recycled at the end of their useful life.

With reduced energy and resources consumption, remanufacturing is the ultimate form of recycling where products are restored to like-new conditions [162] [163]. Remanufacturing can preserve as much as raw materials and added-value by reused in a new product life cycle. The superior ecological and economic advantages of remanufacturing attract the attention from manufacturing companies. However, it is usually not acceptable to the customers that the returned products are directly reused. In addition, due to technological innovations, diverse product characteristics, and changing customer requirements, obsolesce in products and their components make it more difficult for remanufacturing companies to make end-of-life product upgrading decisions. This provides motivation for researchers to develop a methodology to determine the end-of-life product upgrading strategies under design constraints in conjunction with heterogeneous customer preferences.

In product design and development, product designers must identify and convert customer requirements to specific engineering requirements. The customer needs are converted into a set of functional requirements that will eventually be satisfied by the design parameters within the technical and economic constraints of the manufacturing environment. The objective of this work is to capture heterogeneous customer preferences in the product lifecycle design for determining optimal product upgrading strategies of remanufactured products. These are real concerns in practice that the product lifecycle design literatures have not address yet, and that need to be incorporated to improve the product take-back system efficiency. The mixed logit model is utilized to build the demand model that takes into account heterogeneous customer preferences and competition in different market segments. The product upgrading design decision model is proposed to associate with the demand model.

The remainder of this chapter is outlined as follows: the second section presents our optimization models in detail. In the third section we describe our case study and preparation for the simulation, and in the fourth section we present our simulation results. The final section concludes this chapter.

7.2 Problem Formulation

A product design problem can be formulated as the general optimization problem as follows:

$$max \;\; \boldsymbol{f}(\boldsymbol{x}) \tag{7.1}$$

Subject to

$$\boldsymbol{g}(\boldsymbol{x}) \leq \mathbf{0} \tag{7.2}$$

$$\boldsymbol{h}(\boldsymbol{x}) = \mathbf{0} \tag{7.3}$$

$$\boldsymbol{x}_{min} \leq \boldsymbol{x} \leq \boldsymbol{x}_{max} \tag{7.4}$$

Where $\boldsymbol{x}$ is the vector of design variables. The objective function $f(\boldsymbol{x})$ for the design problem can be engineering performance measures or business goals, such as profit, market share, and so on. Based on the assessment of customer needs and the technical specifications, different design alternatives or design variables are evaluated to achieve the optimal design. If a product design model includes an evaluation criterion, then it is a decision making model [164]. Meantime, the design alternatives should be subject to the constraint set, which includes equality constraints $\boldsymbol{h}(\boldsymbol{x})$, inequality constraints $\boldsymbol{g}(\boldsymbol{x})$, and design variable bounds ($\boldsymbol{x}_{min}$, $\boldsymbol{x}_{max}$).

As we mentioned earlier, remanufacturing is an attractive way of recapturing as much of the economic and ecological value as possible from already manufactured and used products. However, remanufacturing also put extra design constraints to the product upgrading design decisions. Successful product remanufacturing is conducted on the basis of keeping original design variables and parameters ($\boldsymbol{x}_{\boldsymbol{Input}}$) as shown in equation (7.6). To achieve the optimal product upgrading strategy, it is necessary to consider the vector of design variables $\boldsymbol{x}$ and the end-of-life phase component level decisions simultaneously as shown in equation (7.5). A binary vector $\boldsymbol{y}$ determines whether the added-value on a component where materials, energy, and labor were invested to manufacture in previous life cycle needs to be recovered. Changing the design variable values in the given model may cause end-of-life component or modules impossible to be remanufactured.

$$max \quad \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y}) \tag{7.5}$$

Subject to

$$\boldsymbol{x_0} = \boldsymbol{x_{Input}} \tag{7.6}$$

$$\boldsymbol{g}'(\boldsymbol{x}) \leq \boldsymbol{0} \tag{7.7}$$

$$\boldsymbol{h}'(\boldsymbol{x}) = \boldsymbol{0} \tag{7.8}$$

$$x_{min} \leq x_i \leq x_{max} \quad i = 1, \dots, I \tag{7.9}$$

In this work, the model is formulated as a mixed integer programming optimization problem for optimal upgrading design decision for remanufactured products. The objective of product upgrading design decision problem for manufacturers is to maximize the profits from remanufactured products in the market with customers who have heterogeneous preferences. Estimation of demand is the key question in differentiated products markets. With better estimates of demand, we can measure the benefits from upgrading remanufactured products.

$$f(\boldsymbol{x}, \boldsymbol{y}) = Q(P - C_V - C_F) \tag{7.10}$$

In equation (7.10), the product price (P) is the sum of total upgrading and remanufacturing costs and profit per unit; profit per unit included in the final price is specified for the targeted market segment. Market share, the percentage or proportion of the total market segment size that is being captured by a manufacturing company, is used to measure of business performance for the manufacturers.

The estimation of upgrading and remanufacturing costs is expressed as the sum of variable upgrading costs ($\mathrm{C_V}$) and fixed costs ($\mathrm{C_F}$). The variable costs are a function of decision variables in term of material costs, labor costs, and end-of-life reprocessing costs, which are discussed in detail later. Fixed costs $\mathrm{C_F}$, such as fixture and setup costs, tooling cost, and investment costs, are treated here as constant for simplicity.

In order to accurately estimate the demand Q, random coefficient logit model, Mixed Logit model (MXL) [165] [166], can be used to analyze the discrete choices made by individuals. Mixed Logit models have been developed and applied in many research areas that can avoid the limitations of standard logit model by "allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time." [111] In the Mixed Logit model, the utility that decision maker n obtains from any alternative j is U_{nj}, which can be decomposed into several parts as shown in equation (7.11):

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \gamma Z_{nj} + \beta_n^T X_{nj} + \varepsilon_{nj} \tag{7.11}$$

Where the systemic component of utility V_{nj} includes two parts: γ is a vector of fixed coefficients (the same for all customers in one market segment) of variables Z_{nj}, and a vector of random coefficients β_n (different for each customer in one market segment) of variables X_{nj}. ε_{nj} is the stochastic factor, which takes into account all the variables that have an effect on the utility function. Z_{nj} and X_{nj} are the observed design matrix that may include both choice-specific and individual-specific variables, such as price, product attributes, and so on. The stochastic part ε_{nj} is assumed to have an extreme value distribution.

In the equation (7.12), β_n is specified to be random variables, which differs across customers, capturing the taste heterogeneity in the population. If the probability density function for β'_n is fixed, then the probability of choosing alternative j is the integration of logit probabilities over the density of parameters.

$$P_{nj} = \int L_{nj}(\beta) f(\beta)\, d\beta \tag{7.12}$$

Where $L_{nj}(\beta)$ is the logit probability over parameter β, and $f(\beta)$ is its probability density function. The parameters that describe the density of β_n are θ, such as the mean (μ) and covariance matrix (Σ), so the density can be denoted as $f(\beta|\theta)$.

$$L_{nj}(\beta) = \frac{e^{V_{nj}(\beta)}}{\sum_{j=1}^{J} e^{V_{nj}(\beta)}} \tag{7.13}$$

The presence of a standard deviation of β accommodates the presence of unobserved preference heterogeneity in the sampled population [167]. The challenge for preference heterogeneity is that the distribution of parameters is unknown.

We assume that manufacturers can take their sold products back for end-of-life management through leasing or other extended producer responsibility mechanisms. When it reaches the end of one lifecycle before it can be remanufactured, a product starts from disassembly, which is a process physically separates an assembled product into parts and/or subassemblies. In this process, some parts or components become waste, others are inspected for damage, repaired, or replaced broken parts, inspected again before it can be reused in the new product life cycle. Each component is then carefully reassembled.

In this case, the possible design decision we consider in the study for component c is a binary integer decision variable (y_c) – remanufacturing or new. If the returned component is not remanufactured in any form and need to be disposed, a new component is produced either with the original product design parameters or with upgraded design to include the latest design enhancements and improvements. Remanufactured components or modules are typically treated to have the same or similar performance and quality standard as the new ones.

$$y_c = \{0,1\} \qquad c = 1, \dots, C \tag{7.14}$$

The disassembly process is not simply the reverse of assembly process. A number of studies have shown that complete disassembly is infeasible and ineffective in product end-of-life management. An end-of-life module disassembly matrix (EMDM) [17] was proposed in order to efficiently disassemble products in order to achieve valuable end-of-life modules. In this work, the end-of-life components or modules are just as given ($c = 1, \dots, C$).

The variable costs C_V are dependent on the manufacturing process, including material costs ($C_{material}$), labor costs (C_{labor}), end-of-life reprocessing costs (C_{eof}) depending upon design variables ($\boldsymbol{x}$) and end-of-life decisions ($\boldsymbol{y}$), as shown in equation (7-15).

$$C_V = C_{material} + C_{labor} + C_{eof} \tag{7.15}$$

Manufacturers are assumed to be required to provide responsible disassembly and end-of-life management (including recycle or disposal) in the case study. The end-of-life reprocessing costs include several parts: average collection costs $C_{transport}$, disassembly costs $C_{diassembly}$, assembly costs $C_{assembly}$, remanufacturing costs ($C_{remufacturing}$), and/or disposal and dumping costs ($C_{disposal}$), as in equation (7-16). Collection costs are assumed to be constants, since the optimization of reverse logistics in product take-back systems is out of the scope of this paper. If a component can be remanufactured, $C_{c,remufacturing}$ represents corresponding costs in the industrial recovering process in which a worn-out or discarded product is restored to like-new condition. On the other hand, the component will be disposed ($C_{c,disposal}$) and replaced with a new component in the next lifecycle ($C_{c,material}$, $C_{c,disposal}$).

$$C_{eof} = C_{transport} + C_{diassembly} + C_{assembly} + C_{remufacturing} + C_{disposal} \tag{7.16}$$

$$C_{remufacturing} + C_{disposal} = \sum_{c=1}^{C} C_{c,remufacturing} y_c + (1 - y_c)\, C_{c,disposal} \tag{7.17}$$

$$C_{material} + C_{labor} = \sum_{c=1}^{C} (C_{c,material} + C_{c,labor})(1 - y_c) \tag{7.18}$$

After the returned products are collected, specific component or modules need to be replaced with remanufacturing services or redesigned. The binary decision variable y_c of each component or module will put additional constraints to the optimization problem. When the component is remanufactured, the design variable $x_{i'}$ keeps the input value ($\boldsymbol{x_{Input}}$) from previous life cycle, as shown in equation (7.19). S is the set of components that direct influence design variables i'.

$$y_c x_{i'} = y_c x_{input,i'} \qquad c \in S\{i'\} \tag{7.19}$$

7.3 Case Study

There are many products that are being remanufactured in the market [168]. To describe the validity of the constructed model, a power tool – an electric power drill is used here to demonstrate the proposed approach. Electric drill is designed to use various bit sizes in order to drill holes and drive screws through a number of materials. Electric drills are technologically mature products, and a large fraction of returned products can be reused after remanufacturing. According to WRAP's Environmental Assessment of Electrical Products, 91% of a household drill's environmental impact occurs in the materials and processing phase, and only 2% occur in use [169]. Therefore, remanufacturing electric drills can limit environmental impacts, and is a key strategy to achieve sustainable manufacturing.

Figure 7-1: Power Drills/Driver (Source: Amazon.com)

The drill, which is run by a universal motor, works by converting electrical energy to mechanical energy. A power drill is comprised of mechanical and electrical two sub-systems. The mechanical subsystem includes components that can transfer, translate and apply forces. The electric subsystem includes components that supply and control power flow. The variables that influence customers choosing an electric drill are described as follows:

1) Price, in dollars, is the quantity of payment of a customer that would like to pay for an electric drill.

2) Weight, the unit of which is often taken to be kilograms (kg).

3) Power, which is the rate at which energy is transferred, used, or transformed. The higher the power, the more powerful the drill is. The input power of the universal motor is used to in the case study. The unit of power is watt (W).

4) Torque, which is the measurement of twisting force when the drill is in use mode. It represents how powerful the drill is, which is measured in Newton-meters (Nm).

5) Remanufactured dummy. This variable is used to represent whether product is labeled as ‘‘new’’ or ‘‘remanufactured”, which is produced in the process of disassembly and recovery at the module or component level. This label affects consumer’s perception of value.

6) Energy efficiency, which is the ratio of its useful power output to its total power input and is usually expressed in percentage (%). The energy efficiency of the universal motor is used to in the case study.

7) Chuck size. The chuck is the mechanism that holds the drill bit securely in place. Chuck size dictates the largest size of bit or other accessory the drill can take. For example, if a drill rated at 1/4", it means that this is the largest-diameter shank that will fit the chuck and indicates the largest-sized hole recommended to be drilled with a 1/4" bit in 1/4" thick mild steel [170].

In this work, several electric drills were selected that were broadly representative of two hypothetical market segments. These data were collected from some real products in the current electric drill market. Customers in each market segment are selecting to purchase an electric drill from the following several alternatives. In each market segment, a customer faces a choice among five product alternatives ($A_1, \dots, A_5$ and $B_1, \dots, B_5$) as shown in Table 7-1. In addition, customer does not necessarily choose any of the alternatives from the set. It implies that customer may not choose to buy at all.

Table 7-1: Product competitors in the hypothetical electric drill market segment 1

	Price	Weight	Power	Torque	Remanufactured	Efficiency	Chuck Size
A_1	95.49	2.54	780	12.22	0	48	1/2"
A_2	73.29	1.94	734	11.96	0	54	1/2"
A_3	53.31	1.67	552	6.18	0	56	3/8"
A_4	49.78	1.50	520	4.18	0	58	3/8"
A_5	39.65	1.30	306	3.05	0	61	3/8"

Table 7-2: Product competitors in the hypothetical electric drill market segment 2

	Price	Weight	Power	Torque	Remanufactured	Efficiency	Chuck Size
B_1	79.22	1.62	450	5.75	0	66	1/2"
B_2	58.99	1.18	420	4.12	0	68	3/8"
B_3	43.79	1.09	360	2.84	0	70	3/8"
B_4	34.89	0.91	300	1.40	0	72	3/8"
B_5	25.68	0.76	180	0.60	0	76	3/8"

There are approximately 20 main components and about more than 10 small parts. The major functioning parts of this product are listed in the table. Each major component of the drill is analyzed and material and manufacturing process are discussed in the table. Some small components, such as wire bracket and trigger lock, are not discussed in here. The power travels through the power cord and goes into the stator. There are windings in the stator and in the rotor that create a magnetic field. The commutator is to control the direction of the current. The torque created from the rotor is transferred to a set of gears, which are used to amplify the torque from the rotor and in effect drive the drill bit. The fan, which is between the motor and gears, is used to cool down the system and provide a default load, preventing the motor from spinning too fast and damaging itself. The chuck is capable of holding drill bits that fall within the size of the chuck.

Table 7-3: Major component of the drill and its material and manufacturing process

Part #	Part	Quantity	Material	Manufacturing Process
1	Housing	2	Plastic and rubber	Injection Molding
2	Chuck	1	Plastic and Metal core	Metal Casting and Injection Molded
3	bit	1	Metal	Machined
4	Motor Shaft	1	Metal	Machined
5	Commutator	1	Metal (Copper)	Machined & Sheet Metal Forming
6	Rotor	1	Copper Wire, Metal Core	Wire wound around the Die Cast Core
7	Brushes	2	Carbon	Molded
8	Brush Holders	1	Metal	Sheet Metal Forming
9	Stator Coils	1	Copper Wire	Copper Wire is wound around the Core
10	Stator Core	1	Metal	Die Cast
11	Cooling Fan	1	Plastic	Injection Molding
12	Gearbox	1	Various	Various
13	Switch	1	Plastic	Injection Molding
14	Rear Plate	1	Plastic	Injection Molding
15	Trigger	1	Plastic	Injection Molding
16	Grips	1	Rubber	Injection Molding
17	Power Cord	1	Insulated Metal	Extruded and Injection Molded
18	Screws	10+	Metal	Metal Casting

Universal electric motors are commonly employed in electric hand-held drilling machines, which require high torque to drill objects under heavy loads at a low operating speed. In a universal motor, both the rotor (armature) and stator are created by electromagnetic effects. With this relationship, the two magnets begin to repel each other, which cause the rotor to turn. The brushes transfer electricity to the motor shaft, which causes it to turn. As the shaft rotates, it causes the gears to turn as well, which then makes the drill bit rotate.

The universal electric motor design problem formulation is mainly referred to the research works done by Simpson et al. [19] [171]. In addition, we referred to other research papers, such as [172] [173] [174] [175] [176], to more accurately estimate the design parameters and performance in the universal motor. The detailed discussions about the mathematical model for the design of universal electric motor, includes the design variables ($x_1, \dots, x_8$), design constraints, and performance measure of the universal motor, can be found in the references above. The terminal voltage is fixed to 115 volts.

Design variables and Bounds:

x_1: Number of wire turns on the motor armature ($100 \leq x_1 \leq 1500$ turns)

x_2: Number of wire turns on each field pole ($1 \leq x_2 \leq 500$ turns)

x_3: Cross-sectional area of the armature wire ($0.1 \times 10^{-6} \leq x_3 \leq 1 \times 10^{-6}\ m^2$)

x_4: Cross-sectional area of the field wire ($0.1 \times 10^{-6} \leq x_3 \leq 1 \times 10^{-6}\ m^2$)

x_5: Radius of the motor ($0.01 \leq x_5 \leq 0.1m$)

x_6: Thickness of the stator ($0.005 \leq x_6 \leq 0.1m$)

x_7: Current drawn by the motor ($0.1 \leq x_7 \leq 6\ Amp$)

x_8: Stack length ($0.01 \leq x_6 \leq 0.2m$)

$x_{9:}$ The first gear ratio in gear reduction ($0 < x_9$)

$x_{10:}$ The second gear ratio in gear reduction ($0 < x_{10}$)

x_{11}: Chuck size ($x_{11} = \frac{3}{8}\ \ or\ \frac{1}{2}$ inches)

Design constraints:

Magnetizing Intensity (H): H ≤ 5000 Amp.turns/m (7.20)

Feasible Geometry: $x_5 < x_6$ (7.21)

Motor Power (P): P=300 W (7.22)

Motor Torque (T_m): T = {0.05, 0.1, 0.125, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5} Nm (7.23)

Efficiency (η): $\eta \geq 0.15$ (7.24)

Motor mass (M_m): $M_m \leq 2.0kg$ (7.25)

The universal optimization problems are described in detail by Simpson et al. [171], [173–176] along with the explanation of the model and the optimal design parameters in the product platform. In this work, we assume the design variables and performance measure for the universal motor as given.

The power from an electric motor is transmitted to the drill bit by the gears, which can convert the high speed/low torque output of the motor to a lower speed/high torque which is preferred. Gear pairs are mounted on shafts and are grouped according to tooth forms and shaft arrangement. Spur gears are typically used in electric drills, with an efficiency of 98-99%. The power loss through gear reduction is negligible. Only double reduction gears are considered in this case study. Therefore, for a gear pair, the output power is assumed to equal to the input power, as shown in equation 7.26, where power is the product of torque and angular velocity. So this results in equation 7.27.

$$P_{input} = P_{output} \tag{7.26}$$

$$T_{input}\omega_{input} = T_{output}\omega_{output} \tag{7.27}$$

Rearranging equation 7.27 gives equation 7.28

$$\frac{T_{output}}{T_{input}} = \frac{\omega_{input}}{\omega_{output}} \tag{7.28}$$

Since the linear velocity of the two gears is the same, angular velocity of a gear is inversely proportional to its radius, which is proportional to the number of teeth on the gear. Therefore, the torque of a gear is proportional to the number of teeth the gear (N) has, as shown in equation 7.29. In this case study, double reduction gear system is used to reduce the speed and also increase the torque output.

$$\frac{T_{output}}{T_{input}} = \frac{N_{output}}{N_{input}} \tag{7.29}$$

In most cases, motor and chuck sizes tend to fall within the following ranges: 1/4 inch (6mm) around 230/240 Watts, 3/8 inch (10mm) within 350/500 Watts and 1/2 inch (13mm) between 700/1000 Watts.

In order to achieve valuable end-of-life modules, several metrics of diassemblabiltiy have been proposed in many research papers. For the electric drill, the detailed disassembly and reassembly procedures were not discussed here. The disassembly time estimation can be found in research works, such as [115] [177].

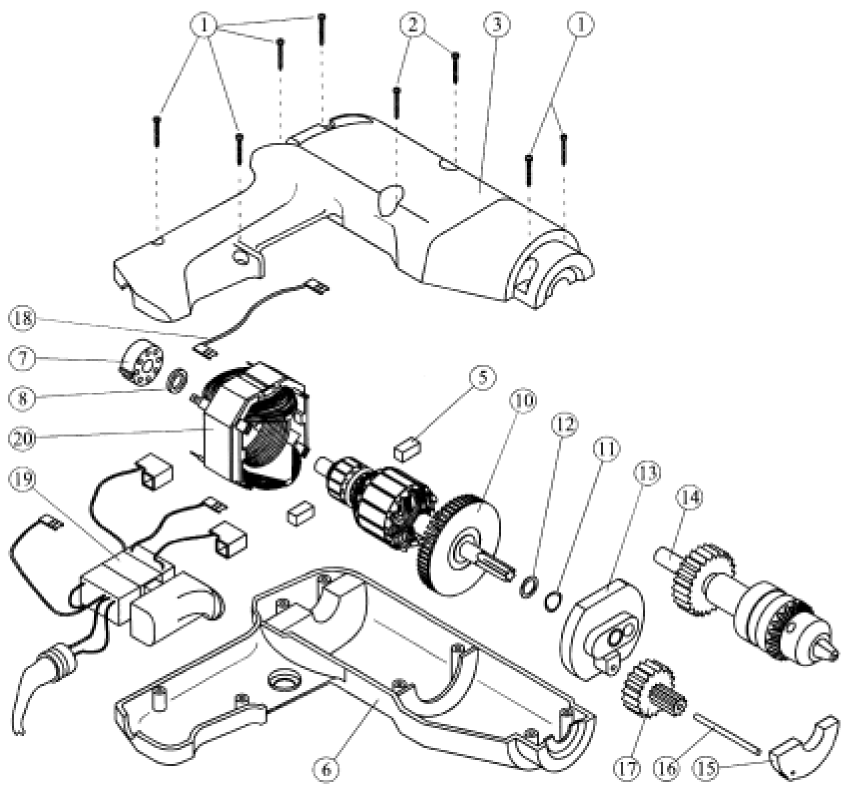


Figure 7-2: The exploded view of disassembled electric drill (adopted from: Kroll and Carver [115]**)**

The main end-of-life parts and modules include:

y_1: Housings

y_2: Chuck

y_3: Bit

y_4: Motor Assembly

y_5: Cooling Fan

y_6: Gear Assembly

y_7: Switch

y_8: Trigger

y_9: Cord

After we remanufacture and upgrade the components, manufacturers need to assemble the electric drill and test it to be in working order.

7.4 Simulation Results

In order to estimate the coefficients in mixed logit model, which are assumed to be random variables that vary from one individual to another, it requires information about customers' preferences in the current marketplace. The main goal of the analysis is to estimate the population parameters $\boldsymbol{\theta}$ that describe the distribution of the individual customer parameters.

Survey data, conjoint analysis, and sales data from the real market need to be collected. Then we can estimate the multidimensional integrals that define the choice probabilities using Monte Carlo simulation. In the simulation, random numbers from the relevant joint probability distributions are drawn, and form an estimate of the choice probabilities. The iteration process repeats this many times to search for the maximum simulated likelihood function, and then averages the results. This average is an unbiased estimate of the choice probabilities. Although it is very computationally intensive to estimate the mixed logit models, an increasing number of software and tools have been developed and used by researchers and practitioners [178], [179].

The coefficients for price, weight, power, and torque are linearized, in which the partworths represent the value of a one-unit increment. The partworths of price and weight are expected to be negative. In the simulation, methods such as transformations of normally distributed terms [180] can be used to make sure the coefficient to more accurately.

Two dummy variables are created to model “remanufactured” and “chuck size”. The dummy variable takes the values 0 or 1 to indicate the absence or presence of some categorical effect that may be expected to influence the outcome. For remanufactured, the new product is taken as the base, and the remanufactured products are taken as increment. For chuck size, the 3/8 inch is taken as the base, and 1/2 inch is taken as the increment.

In this case study, we assume one manufacturer aims at two different markets. The manufacturer produces new products in the first period and has the opportunity to produce new and/or remanufactured products in future periods. We give the hypothetical estimated mean of the coefficients in those two market segments as shown in Table 7-4. The variance and correlation of the coefficients are omitted from the table.

Table 7-4: Mean of partworths of electric drill choice in two market segments

Coefficients	Market Segment 1	Market Segment 2
Price	-0.104	-0.141
Weight	-0.175	-0.489
Power	0.225	0.129
Torque	0.271	0.073
Remanufactured	-1.500	-0.050
Efficiency	0.083	0.994
Chuck Size	0.494	0.093

The mean partworth associated with price, weight, and remanufactured are negative. It is self-explanatory, because it implies that customers prefer cheaper, lighter, and new products. In addition, the customers in the first market segment prefer high power and high torque electric drills, while the customers in the second market segment are more sensitive to the price and weight compared with those in the first market segment.

Once we estimate the parameters in the model, the probability that a product can be adopted in this market segment can be forecasted based on equation (7.13), which is conditional on the mean of β. First, the model is used to estimate the market shares or existing product alternatives in the market. Table 7-5 provides the forecast results for existing product competitors in those two market segments using the models we discussed earlier. The results reflect the forecasted probabilities or market shares for each product alternatives that can be adopted by customers in that market segment. The market shares vary for different product alternatives. In general, we can see that powerful and high torque products are more popular in market segment 1, and products with high efficiency and lower price are more likely to be adopted in market segment 2. A_0 and B_0 represent the probability that customer will not select any of the product alternatives in that market segment. For example, 5.21% of customers in market segment 1 will not select any of the five product alternatives $A_1, \dots, A_5$.

Table 7-5: Market share estimation with existing product competitors (new product only)

Market Segment 1	Market Share	Market Segment 2	Market Share
A_0	5.21%	B_0	16.78%
A_1	24.36%	B_1	9.83%
A_2	32.06%	B_2	14.31%
A_3	14.56%	B_3	17.33%
A_4	13.95%	B_4	20.06%
A_5	9.86%	B_5	21.70%

Next, the model is implemented to predict the market shares of designing two new products separately in those two market segments. As shown in Table 7-6, the market shares of new product alternatives P_1 and P_2 are 21.97% and 19.65% separately. Product P_1 ranks second in market segment 1 in terms of market shares, only next to product A_2. Product P_2 ranks number one in market segment 2 and is better than all other competitors in terms of market shares.

Table 7-6: Market share estimation with introducing new product in two market segments

Market Segment 1	Market Share	Market Segment 2	Market Share
A_0	4.07%	B_0	13.48%
A_1	19.01%	B_1	7.90%
A_2	25.01%	B_2	11.50%
A_3	11.36%	B_3	13.93%
A_4	10.88%	B_4	16.11%
A_5	7.69%	B_5	17.43%
P_1	21.97%	P_2	19.65%

Table 7-7 shows the optimal product attributes of two new products designed for the two market segments we discussed earlier. In addition, the optimal design variables are shown in Table 7-8.

Table 7-7: Optimal product attributes in the new products

	Price	Weight	Power	Torque	Remanufactured	Efficiency	Chuck Size
P_1	62.69	1.53	641	10.41	0	46.8	1/2"
P_2	35.32	0.88	353	0.72	0	85.1	3/8"

Table 7-8: Optimal design variables in the new products

Design Variables	Market Segment 1	Market Segment 2
x_1	1319 turns	691 turns
x_2	68 turns	70 turns
x_3	0.256 mm^2	0.241mm^2
x_4	0.256 mm^2	0.241mm^2
x_5	2.69 cm	1.7 cm
x_6	9.22 mm	4.24 mm
x_7	5.58 Amp	2.97 Amp
x_8	2.12 cm	1.9 cm
x_9	8:35	8:35
x_{10}	10:47	10:33
x_{11}	1/2"	3/8"

Our model further takes into account how to achieve optimal upgrading strategies for remanufactured products. The products P_1 and P_2 from previous analysis are given as the input for the remanufactured products. Product remanufacturing is conducted on the basis of design variables and parameters of P_1 and P_2 as shown in Table 7-8. After product taking-back after the product first life cycle, two remanufactured products will be upgraded as R_1 and R_2. Competing with their corresponding new product alternatives in the market, their market shares in the respective market segments greatly decrease. As shown in Table 7-9, R_1 has only a market share of 6.80%, the second lowest in market segment 1; and R_2 has a market share of 13.38%, the third lowest in market segment 2. It is obvious that remanufactured products have much lower market shares and are much less competitive compared with new products in the original market segment.

Table 7-9: Market share estimation with providing remanufactured product in two market segments

Market Segment 1	Market Share	Market Segment 2	Market Share
A_0	4.86%	B_0	14.53%
A_1	22.71%	B_1	8.51%
A_2	29.88%	B_2	12.39%
A_3	13.57%	B_3	15.01%
A_4	13.00%	B_4	17.37%
A_5	9.19%	B_5	18.79%
R_1	6.80%	R_2	13.38%

In order to improve the competitiveness of remanufactured products and make remanufacturing profitable, the optimal strategies of simultaneously providing combinations of new and remanufactured products in different market segments also need to be addressed. Different combinations of remanufactured products and new ones are projected into market segment 2 in which customers prefers products with lower costs and can accept products with relatively lower performance parameters.

The first strategy is shown in the left half of Table 7-10. In addition to the new product P_2, an upgraded product R_3 remanufactured from product P_1 is also included to target market segment 2. The market shares of these two add up to 26.72%, which is larger than any other competitors in this market segment. The second strategy is to combine two upgraded products remanufactured from previous returned products in market segment 2. As shown in the right half of Table 7-10, R_2 remanufactured from product R_2 and R_3 remanufactured from product P_1 both targets market segment 2. They together have a market share of 21.44%, which is higher than the new product P_2 (19.65%). These two examples indicate that by combining with new products or remanufactured products, remanufactured products can complement new products and help to capture more market shares in certain market segment. Table 7-11 shows the optimal product attributes of the three remanufactured products designed for the two market segments. In addition, the optimal end-of-life design variables are shown in Table 7-12.

Table 7-10: Market share estimation with providing combination of new or remanufactured product in two market segments

Market Segment 2	Market Share	Market Segment 2	Market Share
B_0	12.29%	B_0	13.16%
B_1	7.20%	B_1	7.71%
B_2	10.48%	B_2	11.23%
B_3	12.70%	B_3	13.60%
B_4	14.70%	B_4	15.74%
B_5	15.90%	B_5	17.02%
P_2	17.92%	R_2	12.11%
R_3	8.80%	R_3	9.43%

Table 7-11: Optimal product attributes for remanufactured products

	Price	Weight	Power	Torque	Remanufactured	Efficiency	Chuck Size
R_1	48.32	1.53	641	10.41	1	46.8	1/2"
R_2	32.49	0.88	353	0.72	1	85.1	3/8"
R_3	38.82	1.53	641	10.41	1	46.8	1/2"

Table 7-12: Optimal EOL decision variable (y) for remanufactured products

EOL decision variable	$\boldsymbol{R_1}$	$\boldsymbol{R_2}$	$\boldsymbol{R_3}$
y_1	New	New	New
y_2	New	Remanufacturing	New
y_3	New	New	New
y_4	Remanufacture	Remanufacturing	Remanufacturing
y_5	New	New	New
y_6	New	New	New
y_7	Remanufacturing	Remanufacturing	New
y_8	Remanufacturing	Remanufacturing	New
y_9	Remanufacturing	Remanufacturing	New

7.5 Chapter Conclusions

In this chapter, we proposed a market-driven optimization model to determine optimal product upgrading strategies for remanufactured products associated with dealing with heterogeneous customer preferences in different market segments. We discussed the importance and benefits of product upgrading strategies in product remanufacturing that would help manufacturers expand more market shares. Then we formulate the mathematical model by simultaneously considering the vector of design variables and the end-of-life phase component level decisions under design constraints and end-of-life reprocessing constraints.

Along with recommendations for implementation of the product upgrading strategies for the product recovery, the paper also examined the impact of different product combination on their market shares in specific market segments. To make the product take-back system more efficient, these results of this study should be converted to design guidelines in design phase to facilitate future remanufacturing and recycling, such as material choice, the complexity of disassembly, product architecture, material or component interface compatibility and so on.

In terms of future work, the management and production planning of product take-back systems are more complex than those in traditional manufacturing systems since there are too many uncertainties faced by the manufacturers. The major uncertainties come from the customer preferences for the remanufactured products along with product evolutions over time. We need to more accurately capture customer preference changes. The higher degree of uncertainty also comes from the stochastic nature of returned products. To overcome these problems, service-oriented leasing where the manufactures sell a service rather than a product can help them control the timing and quantity of recycled products to decrease these uncertainties.

CHAPTER 8 CONCLUSIONS

8.1 Summary of the Results

Planned obsolescence [181] is defined as the process of a product becoming obsolete or non-functional after a certain amount of time in a way that is purposely planned or designed by the manufacturer. It was first developed in the 1920s, and has been applied in many different products. In addition, with the rapid technology advances, this trend becomes even obvious that it is often the case that customers need to dispose their products after a very short period of time. As obsolete products fail to satisfy their needs, customers have to purchase again. In this way, manufacturers can benefit from repeated purchases. They have had little incentive to focus on the end of life products since the profits have based on the number of goods produced and sold. However, this result in a waste of resources and a burden to the environment as discussed earlier.

Environmental concerns, customer awareness, and market competition force manufacturers to make environmentally friendly products and deal with these disposed products at the end of product life cycle. This provides motivation for my thesis to develop methodologies to help manufacturers making design decisions early during the design process that maximize overall life-cycle added-value while minimizing cost and environmental impact. The proposed methodologies presented mathematical models to simultaneously consider initial product sales profits and end-of-life recovery profits. Design decisions in the early stage should not only be based on considerations of initial profit from product sales, but on profit from end-of-life recovery and reuse operations. In addition, product upgrading strategies were proposed to help manufacturers plan ahead to find the proper balance between the need for providing upgraded products best fitting different market segments and the exploitation of the most use of the product recycled from the customers.

Additionally, one of the greatest challenges for environmentally conscious design is how to ensure sustainable production systematically and cost effectively compared with conventional design and manufacturing. Environmentally friendly products often add extra complexity and costs to design and manufacturing. Designers face many conflicting objectives and uncertainties to meet customer demands. Environmentally conscious design requires designers to understand and harness market mechanisms first. One of the key issues is how to position environmentally conscious products in the marketplace. The proposed Bayesian methodologies are applied to integrate market considerations, which can be used to measure attribute weights and identify appropriate market segments in which customers value environmentally conscious design.

The methodology offers a framework where, driven by the interaction of heterogeneous customer preferences, product design decisions and end-of-life decisions are optimized under the constraints of product life cycle design. It can be expected that proposed approaches in this work will play an important role in the product life cycle design. It is envisioned that the models proposed in this work and case study results can provide manufacturers with relevant guidelines and useful insights regarding their optimal decision making in environmentally conscious design.

8.2 Outlook

The existing work can be expanded to include the following issues:

1. Manufacturers encounter situations in which the product design is proposed in the absence of complete knowledge about evolving customer preferences in the future. The uncertainties associated with current and future customer needs present more challenges to the environmentally conscious design. In the future work, this question might be well addressed by new methods and problem formulations. In addition, in order to more accurately simulate heterogeneous customer preferences, survey data need to be collected from different market segments. Analysis of these results using the proposed methodologies in the thesis may better the design strategies under different scenarios.

2. Product upgrading may be integrated with customer decision making in multi-generation choices. Although various approaches have been proposed to integrate the discrete choice model with demand modeling in marketing or engineering decision making, demand modeling is still limited in its ability to predict customer behavior with respect to multi-generation products. A design decision model specifically aiming at upgrading products over multiple lifecycles needs to be proposed and validated.

3. The design problem formulation needs to be extended from single product design to that of a product family. Simultaneously considering multiple market segments could also improve the total market share, thus making product recovery more efficient. This provides motivation for researchers to develop a methodology to determine the end-of-life product platform strategies.

However, most studies dealing with the product platform strategies are limited to product families in a single generation thus not appropriate for decision making for successive generations. In addition, it is necessary to address product variety as well as their evolution of design over time. The goal is to propose a structured methodology to determine the end-of-life product platform strategies across successive generations.

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